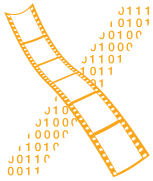

Chair for Computer Science 10 (Media Computing and Human-Computer Interaction)

RWTH AACHEN UNIVERSITY

Dark Patterns in User Interfaces: A Systematic Literature Review and Meta-Analysis

Bachelor's Thesis
submitted to the
Media Computing Group
Prof. Dr. Jan Borchers
Computer Science Department
RWTH Aachen University

by
Anubhav Punetha

Thesis advisor:
Prof. Dr. Jan Borchers

Second examiner:
Prof. Dr. Ulrik Schroeder

Registration date: 11.07.2024
Submission date: 22.10.2024

Eidesstattliche Versicherung
Declaration of Academic Integrity

Name, Vorname/Last Name, First Name

Matrikelnummer (freiwillige Angabe)
Student ID Number (optional)

Ich versichere hiermit an Eides Statt, dass ich die vorliegende Arbeit/Bachelorarbeit/ Masterarbeit* mit dem Titel
I hereby declare under penalty of perjury that I have completed the present paper/bachelor's thesis/master's thesis* entitled

selbstständig und ohne unzulässige fremde Hilfe (insbes. akademisches Ghostwriting) erbracht habe. Ich habe keine anderen als die angegebenen Quellen und Hilfsmittel benutzt; dies umfasst insbesondere auch Software und Dienste zur Sprach-, Text- und Medienproduktion. Ich erkläre, dass für den Fall, dass die Arbeit in unterschiedlichen Formen eingereicht wird (z.B. elektronisch, gedruckt, geplottet, auf einem Datenträger) alle eingereichten Versionen vollständig übereinstimmen. Die Arbeit hat in gleicher oder ähnlicher Form noch keiner Prüfungsbehörde vorgelegen.
independently and without unauthorized assistance from third parties (in particular academic ghostwriting**.** I have not used any other sources or aids than those indicated; this includes in particular software and services for language, text, and media production. In the event that the work is submitted in different formats (e.g. electronically, printed, plotted, on a data carrier), I declare that all the submitted versions are fully identical. I have not previously submitted this work, either in the same or a similar form to an examination body.

Ort, Datum/City, Date

Unterschrift/Signature

*Nichtzutreffendes bitte streichen/Please delete as appropriate

Belehrung:
Official Notification:

§ 156 StGB: Falsche Versicherung an Eides Statt
Wer vor einer zur Abnahme einer Versicherung an Eides Statt zuständigen Behörde eine solche Versicherung falsch abgibt oder unter Berufung auf eine solche Versicherung falsch aussagt, wird mit Freiheitsstrafe bis zu drei Jahren oder mit Geldstrafe bestraft.
§ 156 StGB (German Criminal Code): False Unsworn Declarations
Whosoever before a public authority competent to administer unsworn declarations (including Declarations of Academic Integrity) falsely submits such a declaration or falsely testifies while referring to such a declaration shall be liable to imprisonment for a term not exceeding three years or to a fine.
§ 161 StGB: Fahrlässiger Falscheid; fahrlässige falsche Versicherung an Eides Statt
(1) Wenn eine der in den §§ 154 bis 156 bezeichneten Handlungen aus Fahrlässigkeit begangen worden ist, so tritt Freiheitsstrafe bis zu einem Jahr oder Geldstrafe ein.
(2) Straflosigkeit tritt ein, wenn der Täter die falsche Angabe rechtzeitig berichtigt. Die Vorschriften des § 158 Abs. 2 und 3 gelten entsprechend.
§ 161 StGB (German Criminal Code): False Unsworn Declarations Due to Negligence
(1) If an individual commits one of the offenses listed in §§ 154 to 156 due to negligence, they are liable to imprisonment for a term not exceeding one year or to a fine.
(2) The offender shall be exempt from liability if they correct their false testimony in time. The provisions of § 158 (2) and (3) shall apply accordingly.

Die vorstehende Belehrung habe ich zur Kenntnis genommen:
I have read and understood the above official notification:

Ort, Datum/City, Date

Unterschrift/Signature

Contents

List of Figures and Tables

Abstract

Dark patterns are intentionally designed to exploit users by subtly manipulating the user interface, often resulting in harm. As dark pattern research has expanded across various disciplines, tracking its transdisciplinary development has become increasingly complex. This thesis seeks to review the body of dark pattern research since 2020, with a focus on emerging trends, particularly in examining their impact on users and the development of potential countermeasures.

In conducting a systematic literature review, we adhered to the PRISMA guidelines, examining 52 publications from prestigious conferences and journals. The literature search was conducted between 10 and 25 August, utilising the *Association for Computing Machinery* (ACM) Digital Library, the *Institute of Electrical and Electronics Engineers* (IEEE) Xplore, and a targeted screening of countermeasure-related papers identified in the references of the papers located through these databases.

The dataset was coded to facilitate a meta-analysis, which revealed that certain dark patterns have received more attention in recent years than others. The research community has increasingly concentrated on dark patterns in online shopping interfaces, with studies on other platforms beginning to emerge. We also observed a modest increase in studies focused on specific user groups, such as age or culture-based populations. While damage to user autonomy and personal resources has been extensively studied, harm at the community level remains underexplored. Furthermore, although countermeasure tools aimed at mitigating the effects of dark patterns have become more common, studies involving user interactions with these countermeasures remain relatively sparse.

Überblick

Dark Patterns sind absichtlich gestaltete Elemente, die darauf abzielen, Nutzende durch subtile Manipulationen mittels der Gestaltung der Benutzendenoberfläche auszunutzen, was häufig zu Schäden auf Endnutzenden-Seite führt. Mit der zunehmenden Verbreitung der Dark-Pattern-Forschung über verschiedene Disziplinen hinweg wird es immer komplexer, deren transdisziplinäre Entwicklung nachzuvollziehen. Diese Arbeit hat zum Ziel, die Forschung zu Dark Patterns seit 2020 zusammenzufassen und zu überprüfen, mit einem besonderen Fokus auf aufkommende Trends, insbesondere hinsichtlich ihrer Auswirkungen auf die Nutzenden sowie der Entwicklung potenzieller Gegenmaßnahmen.

Im Rahmen eines systematischen Literaturreviews, das gemäß den PRISMA-Leitlinien durchgeführt wurde, haben wir 52 Publikationen aus hochrangigen Konferenzen und Fachzeitschriften untersucht. Die Literatursuche erfolgte zwischen dem 10. und 25. August unter Einbeziehung von Datenbanken, der *Association for Computing Machinery* (ACM) Digital Library und der *Institute of Electrical and Electronics Engineers* (IEEE) Xplore, sowie einer gezielten Überprüfung von auf *Dark Pattern Countermeasures* gerichteten Artikeln, die in den Referenzen der in diesen Datenbanken gefundenen Publikationen identifiziert wurden.

Der Datensatz wurde codiert, um eine Meta-Analyse zu ermöglichen, die aufzeigt, dass bestimmte Dark Patterns in den letzten Jahren mehr Aufmerksamkeit erhalten haben als andere. Die Forschungsgemeinschaft richtet zunehmend ihren Fokus auf Dark Patterns in Online-Shopping-Platformen, während Studien zu anderen Plattformen allmählich an Bedeutung gewinnen. Zudem konnten wir einen moderaten Anstieg von Studien beobachten, die sich auf spezifische Nutzendengruppen fokussieren. Während die Beeinträchtigung der Autonomie und der persönlichen Ressourcen der Nutzenden bereits umfassend untersucht wurde, bleibt der Schaden auf Gemeinschaftsebene weitgehend unerforscht. Darüber hinaus, obwohl Gegenmaßnahmen zur Minderung der negativen Auswirkungen von Dark Patterns häufiger entwickelt wurden, sind Studien, die die Interaktionen von Nutzenden mit diesen Gegenmaßnahmen untersuchen, weiterhin relativ selten.

Acknowledgments

I want to express my deepest gratitude to Prof. Borchers and Prof. Schroeder for taking the time to examine my thesis.

Furthermore, I am incredibly thankful to my supervisor, Rene Schäfer, for his unwavering dedication, motivation, and invaluable feedback and guidance throughout this journey.

My family, my girlfriend and my friends deserve special thanks for their tireless support during the course of my bachelor's thesis.

Conventions

Throughout this thesis we use the following conventions:

- The thesis is written in British English.
- The first person is written in plural form.

Definitions are set off in colored boxes.

EXCURSUS:
Excursuses are set off in orange boxes.

Where appropriate, paragraphs are summarized by one or two sentences positioned at the margin of the page.

This is a summary of a paragraph.

Literature review codes are formatted in typewriter-style text, and each begins with a capital letter.

`Codebook`

Chapter 1

Introduction

"Deception is one of the quickest ways to gain little things and lose big things."

—Thomas Sowell

Digital technology has become an essential part of everyday

Since the turn of the century, mankind has witnessed noteworthy advancement as digital technology becomes integral to daily life. The number of users on the Internet has increased exponentially in the recent years[1]. With this increase in users, there has been a shift towards the use of online techniques to communicate or access information, leading to a decline in the use of more traditional methods, such as television and newspapers [Babutsidze et al., 2023]. As people worldwide have grown increasingly reliant on the Internet for entertainment and communication [Wellman et al., 2003], business owners have leveraged it to boost their financial value by establishing an online presence [Cheung, 1998]. Given that humans are creatures of greed and often act out of self-interest [D'Souza and Adams, 2016], there is a worrisome trend of designers employing malicious designs in various *user interfaces* (UIs) to manipulate consumers into making decisions that do not serve their best interests [Lupiáñez-Villanueva et al., 2022]. Such unethical designs are commonly referred to as *dark patterns*.

[1] `https://www.itu.int/itu-d/reports/statistics/2023/10/10/ff23-internet-use` [Accessed: September 2024]

Terminology in this thesis

Since our society has pushed for changes in the way we people act and speak to ensure correct political and ethical behaviour[2], some scholars have preferred the term "deceptive patterns" to avoid the negative connotation of "dark" meaning "negative" [Chang et al., 2024]. As the two terms are used as synonyms, throughout this thesis, we would predominantly use the term "dark patterns" as most of the existing literature uses this terminology.

1.1 Dark Patterns

Definition: *Dark patterns*

DARK PATTERNS:
"Dark patterns (also known as “deceptive patterns”) are tricks used in websites and apps that make you do things that you didn’t mean to, like buying or signing up for something." [Brignull et al., 2023]

Users interact with dark patterns, often unconsciously

Dark patterns are not confined to any particular genre of UI. They are omnipresent and span a broad spectrum of platforms, including those for social media [Albuquerque et al., 2024; Mildner and Savino, 2021] and online shopping [Mathur et al., 2019]. Despite various dark patterns having been identified in practice [Gray et al., 2024], dark patterns remain imperceptible for most users, who remain unaware of their presence [Di Geronimo et al., 2020]. Although user awareness of dark patterns has increased, research indicates that it remains in its early stages [M. Bhoot et al., 2021]. Subsequently, the consequences of users falling victim to such devious tricks are diverse. They may range from mild frustration [M. Bhoot et al., 2021] to severe privacy breaches [Bösch et al., 2016], financial repercussions [Mathur et al., 2021] and psychological distress [Lupiáñez-Villanueva et al., 2022].

Dark patterns are a topic of interest in different fields

The term "dark patterns" was first coined by Harry Brignull in 2010 as part of his effort to highlight malicious design practices on the "Hall of Shame" page of his website.

[2] `https://www.acm.org/diversity-inclusion/words-matter` [Accessed: September 2024]

This page featured some of the most popular websites, including Google and Amazon[3]. Since then, the concept of dark patterns has evolved in both its scope and definition. Nearly 15 years after its introduction, research into dark patterns has cultivated an interest across various fields.

Dark patterns in HCI

Within the human-computer interaction (HCI) community, dark pattern research is vast and continually evolving. HCI conferences, such as the *Conference for Human-Computer Interaction* (CHI), have seen a rise in contributions focused on dark patterns in recent years [Lukoff et al., 2021]. These contributions serve distinct yet equally important objectives. For example, there is an ongoing effort is to build a shared taxonomy of dark patterns [Mathur et al., 2021; Gray et al., 2024]. At the same time, other researchers are exploring the impact of dark patterns in different cultural environments, such as Japan [Seaborn et al., 2024] and Germany [Krisam et al., 2021]. Additionally, significant progress is being made in developing automatic dark pattern detection tools, like the Web Crawler [Mathur et al., 2019] and AidUI [Mansur et al., 2023]. Moreover, the conversation has expanded to include "bright patterns", which contradict dark patterns by promoting actions in line with the user's interest [Sandhaus, 2023], along with countermeasures to dark patterns [Vigh et al., 2024; Schäfer et al., 2023]. The latter has emerged as a surging area of focus.

Dark pattern research stretches across various disciplines

Dark patterns have been the subject of substantial interest in the fields of legislation [Kyi et al., 2023], ethics [Van Mechelen et al., 2020] and psychological welfare [Lupiáñez-Villanueva et al., 2022]. Furthermore, they have attracted a substantial audience in the domains of robotics [Lacey and Caudwell, 2020] and gaming [Aagaard et al., 2022]. As dark patterns continue to grab the limelight of diverse research communities, tracking their evolution becomes increasingly challenging. Emerging areas of interest, such as *Virtual Reality* (VR) [Krauß et al., 2024], Human-Computer-Integration [Dickinson et al., 2022], are also now examining dark patterns and pushing the boundaries of research.

[3] `https://www.deceptive.design/hall-of-shame` [Accessed: September 2024]

There is a need to understand the evolution of research

Currently, there is a scarcity of research tracking the evolution of dark patterns across diverse spectra. The rampant growth and vast reach of dark patterns corroborate the need to thoroughly understand the trajectory and future direction of dark pattern research, the potential impact of these dark patterns on users, and possible countermeasures to mitigate them.

Aim of the thesis

Adhering to the guidelines provided in the *Preferred Reporting Items for Systematic Reviews and Meta-Analyses* (PRISMA) statement [Page et al., 2021], we analysed the research gap through research contributions made from 2020 to 2024 across various high-prestige conference venues and journal publications. We further streamlined our focus using the following research questions:

RQ1 What are key trends and developments in the evolution of dark patterns over recent years?

RQ2 How do users perceive and respond to dark patterns across various user interfaces?

RQ3 What countermeasures and strategies have emerged in recent years to mitigate the effects of dark patterns?

RQ4 What are potential future research directions and hot topics in the study of dark patterns?

1.2 Outline

This thesis is structured into five chapters. Following this introductory chapter, Chapter 2 delves into the existing body of work to offer insights into prior research on dark patterns. Chapter 3 describes the research methods used to select and analyse the papers for the literature review. Furthermore, we elaborate on the process used to conduct the literature analysis and present the review findings. In Chapter 4, we provide a detailed evaluation of our findings and conduct an extensive discussion of the results from Chapter 3. Last but not least, we conclude this thesis in Chapter 5 with a summary of its contributions of the thesis and recommendations for future research.

Chapter 2

Related Work

The following chapter offers an overview of research on dark patterns, starting with work from the HCI community. It explores relevant findings, including taxonomies and presently existing dark patterns, and discusses their impact on users and proposed countermeasures. It also covers relevant literature reviews regarding dark patterns within HCI. Then, it examines dark patterns beyond HCI, focusing on legislation, ethics, and psychology. It also examines emerging fields like robotics, gaming, and virtual reality.

2.1 Dark Patterns in HCI

Unethical marketing strategies were researched before the 20th century

Manipulation and deceptive marketing tactics were subjects of research long before Harry Brignull introduced the term "dark pattern". As early as the late 20th century, scholars highlighted unethical marketing practices [Akaah and Riordan, 1990] and methods employed by companies to abuse the cognitive limitations of the users for the companies' own benefits [Hanson and Kysar, 1999]. With the rapid advancement of technology and the growing ease of access and connectivity, these manipulative strategies have evolved into new forms, posing more significant risks to users [Calo, 2013].

Brignull started a widespread discussion on dark patterns

In 2010, Brignull et al. [2023] coined the term "dark patterns" to describe deliberately crafted UIs designed to deceive users. Although Harry Brignull is widely credited with bringing substantial attention to dark patterns and sparking their extensive discussion within the research community, it is essential to note that interest in these deceptive practices had begun to surface in the scientific domain somewhat earlier. For example, Fogg [2002] highlighted the concept of "persuasive technology," which shares similarities with dark patterns. Around the same time as Brignull's effort, there were studies aimed at understanding the rise of intentionally constructed "malicious interfaces" that violate design principles to achieve objectives contrary to users' interests [Conti and Sobiesk, 2010].

Dark patterns are everywhere

Dark patterns can be found in various forms, and their presence is not exlusive to a particular platform like e-commerce [Lupiáñez-Villanueva et al., 2022; Mathur et al., 2019], social media [Albuquerque et al., 2024; Mildner et al., 2023], gaming [Aagaard et al., 2022; Zagal et al., 2013], or safety technology [Chordia et al., 2023]. Two examples from e-commerce and social media are depicted in Figure 2.1. Furthermore, dark patterns have expanded across various UIs, such as mobile devices [Di Geronimo et al., 2020; Hidaka et al., 2023], *communication UIs* (CUIs) [Dubiel et al., 2024; Mildner et al., 2024] and *extended reality* (XR) [Hadan et al., 2024; Krauß et al., 2024].

Politically correct terminology

The term "dark patterns" has emerged under increasing scrutiny. Many experts have criticised the choice of adjective, which possesses a colonialistic association[1]. In response, the research community has preferred to opt for a more acceptable term, such as "deceptive patterns" or "manipulative patterns". In his book, Brignull notes that following advice from the Tech Policy Design Lab of the World Wide Web Foundation, he has opted to use the term "deceptive pattern" to avoid language that might unintentionally carry racist associations [Brignull, 2023].

[1] `https://medium.com/@carolinesinders/whats-in-a-name-unpacking-dark-patterns-versus-deceptive-design-e96068627ec4` [Accessed: September 2024]

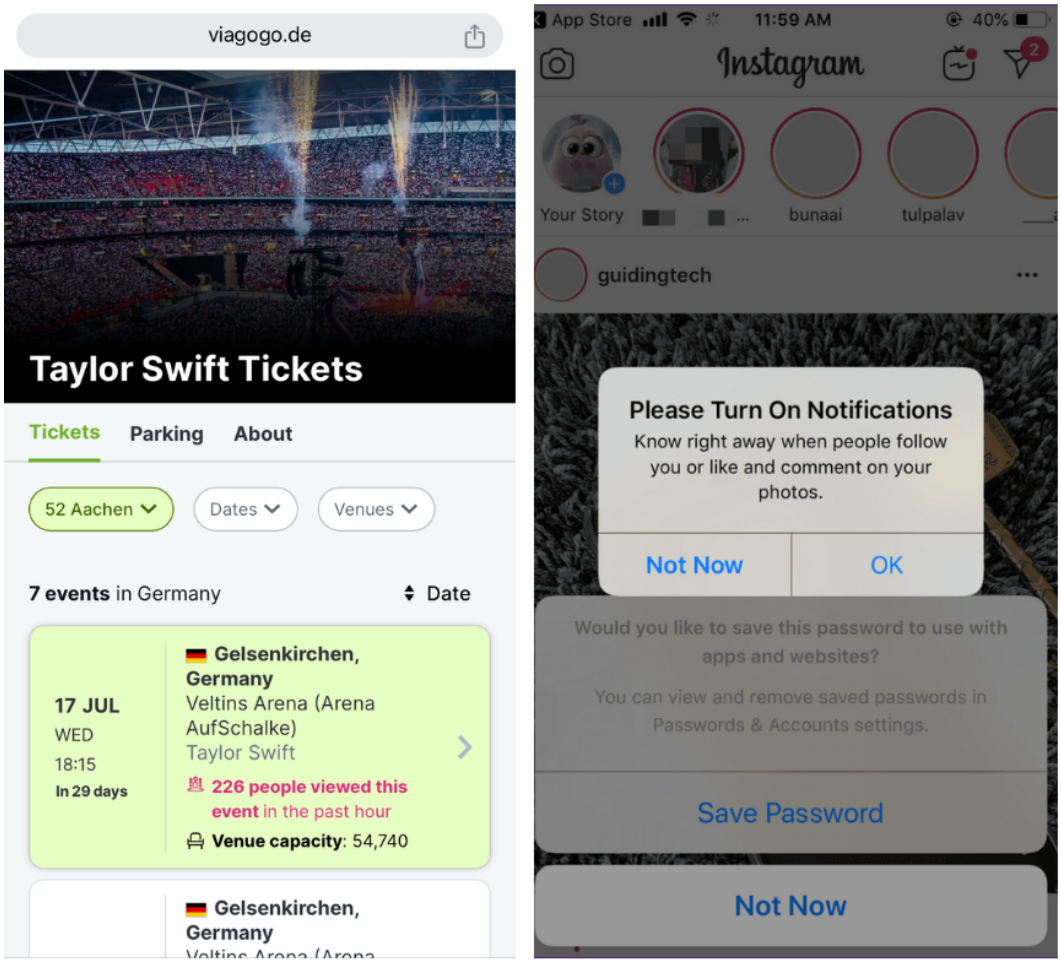

Figure 2.1: Two real-world examples of dark patterns: The left screenshot taken from `https://www.viagogo.de/` [Accessed: June 2024] shows an *Activity Message*, which uses urgency and false information to manipulate users [Gray et al., 2024]. The right screenshot demonstrates *Nagging*, in which users are repeatedly urged to enable notifications, with no option to fully decline. [Brignull et al., 2023]

Diverse interpretations of dark patterns

As interest in dark patterns grows, there has been an exponential rise in the research on and interpretations of dark patterns. Mathur et al. [2021] collected 19 different but similar interpretations of dark patterns in literature published across academic publications and in government materials. The vast and diverse interpretations in research in this field have led to various taxonomies of dark patterns.

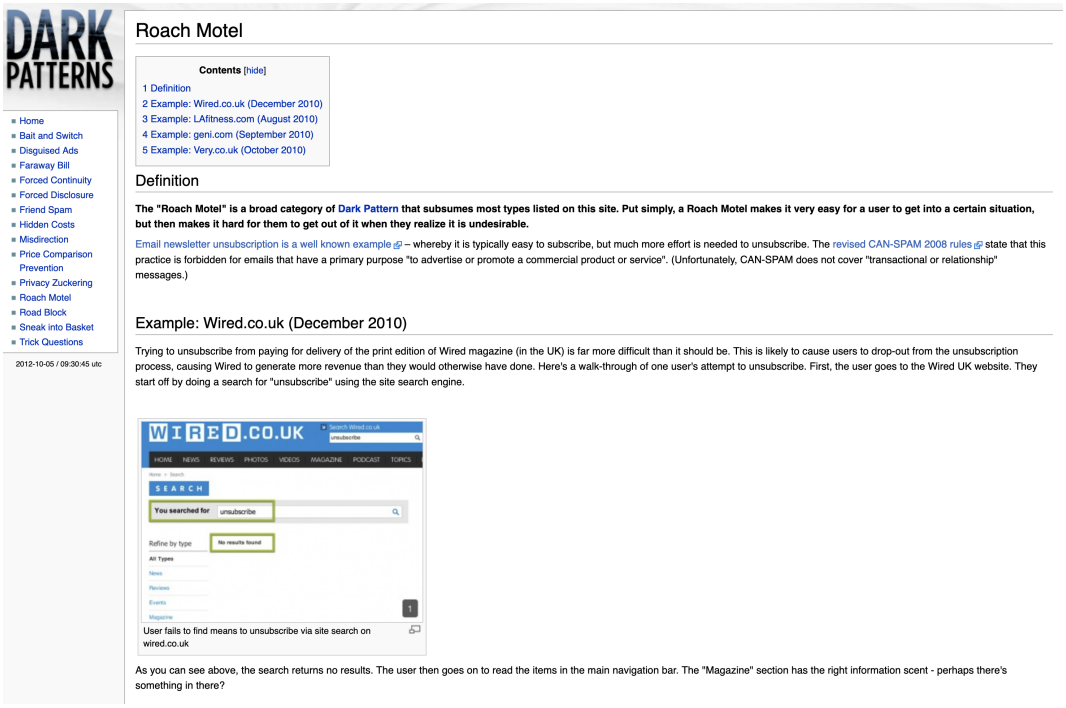

Figure 2.2: The dark pattern *Roach Motel* as described by Brignull in 2010. Users can access the home page and the 14 dark pattern types Brignull defines via the left menu.

2.1.1 Taxonomies

Earliest approaches towards a dark pattern taxonomy

Due to the extensive use of dark patterns, it has become necessary to classify and define them to aid further research. Harry Brignull initially provided one of the first such taxonomies, in which he extensively characterised 14 dark pattern types using visuals and detailed descriptions, such as the *Roach Motel*, *Disguised Ads* and *Price Comparison Prevention*. Fig 2.2 illustrates a screenshot of his old website[2].

Brignull et al. [2023] and Conti and Sobiesk [2010] provided the first taxonomies

Concurrently, Conti and Sobiesk [2010] proposed another taxonomy of malicious interface design techniques based on a year-long study, resulting in 11 categories of malicious interfaces. Though both taxonomies are individual and independent contributions, there are remarkable similarities.

[2] `https://old.deceptive.design` [Accessed: September 2024]

For example, the concept called "distraction" by Conti and Sobiesk [2010] is closely aligned with the one called "misdirection" by Brignull [2010].

Taxonomies are aligned towards a particular domain

As the interest in dark patterns research started to spread rapidly, more and more researchers across different domains started to create taxonomies informed by their different areas of expertise. Bösch et al. [2016] presented an account of dark patterns in the field of privacy in the form of a framework. Zagal et al. [2013], on the other hand, investigated the concept of dark patterns in gaming design. Another valuable contribution was from Mildner et al. [2023], who examined dark patterns on four popular social media platforms (Facebook, Instagram, TikTok and Twitter). They identified five themes characterising these dark patterns, which were then grouped into two overarching strategies, namely *engaging strategy* and *governing strategy*. In the recent past, Lupiáñez-Villanueva et al. [2022] offered a taxonomy based on behavioural sciences mapping dark patterns on two axes: the choice of the architecture and the decision-making process.

Mathur et al. [2019] developed a dark pattern taxonomy after analysing shopping websites

Mathur et al. [2019] investigated dark patterns in the e-commerce sector using an automated web crawler. Their study analysed approximately 53,000 product pages from around 11,000 shopping websites, identifying 1,818 instances of dark patterns. The resulting taxonomy consisted of 15 dark patterns categorised into seven categories, namely *sneaking*, *misdirection*, *urgency*, *social proof*, *scarcity*, *obstruction* and *forced action*. In their later work, Mathur et al. [2021] expanded on their own and various other taxonomies to offer analytical clarity and establish guiding principles for dark pattern research.

Gray et al. [2018] took the first step towards an ontology of dark patterns

At the recently concluded *Conference on Human Factors in Computing Systems* (CHI) conference, Gray et al. [2024] presented an ontology of dark patterns knowledge resulting from the extensive work of prior years. Gray et al. [2018] built on the taxonomy provided by Brignull in 2010 and approached dark patterns from an ethical standpoint. They rearranged the dark patterns discovered by Brignull into five broader categories, depicted in Figure 2.3. They incorporated knowledge from the most noteworthy taxonomies

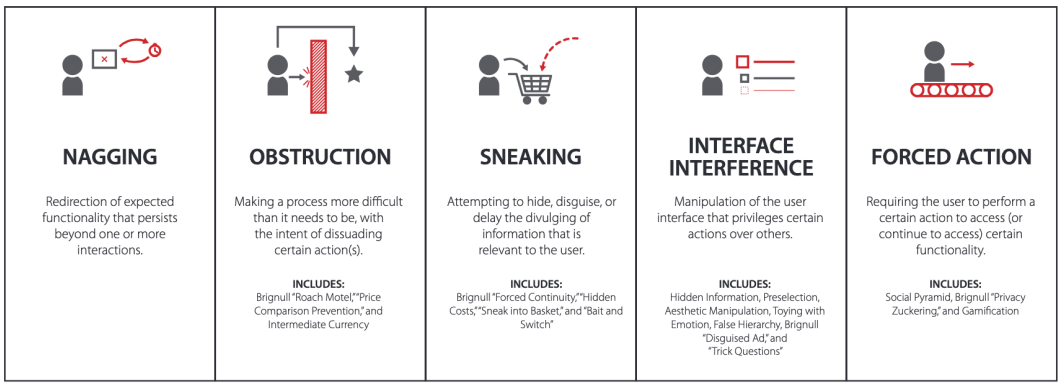

Figure 2.3: The five categories identified by Gray et al. [2018]: *nagging*, *obstruction*, *sneaking*, *interface interference* and *forced actions* and the corresponding reference to the various dark patterns as described by Brignull [2010].

to date across the domains of academics and legislature. The authors are experts in different fields, including HCI, design, law and regulation, making this contribution a trans-disciplinary landmark for future research.

Gray et al. [2024] introduced standardised definitions for 65 dark patterns

Through an extensive five-step process Gray et al. [2024] created a framework that included five high-level patterns, 25 meso-level patterns and 35 low-level patterns. They also introduced standardised definitions for these 65 dark patterns, building a foundation for future research that should aid future researchers in identifying existing or new dark patterns across different domains.

2.1.2 Impact on Users

Dark patterns harm the users through manipulation

Despite the diversity of definitions of dark patterns gathered by Mathur et al. [2021], all definitions tend to describe dark patterns as a careful forms of manipulation in UIs against the user's best interests. These manipulations may harm the user in various forms, such as causing direct financial loss, invading the user's privacy or influencing the user's cognitive perception [Narayanan et al., 2020].

Classification of harms to consumers

Mathur et al. [2021] aimed to classify the emerging ethical concerns into four different perspectives, namely *individual welfare*, *community welfare*, *regulatory objectives* and *individ-*

ual autonomy. Building on the elemental work of Mathur et al. [2021], the *Organisation for Economic Co-operation and Development* (OECD) identified six consumer harms caused by dark patterns, categorising them into three overarching groups, namely *harms to consumers autonomy*, *personal consumer detriment* and *structural consumer detriment* [OECD, 2022].

Various dark patterns impact consumers in different ways

The prevalence of dark patterns across various platforms and interfaces creates the necessity of understanding how and what elements impact users and whether there are means to mitigate this harm. Luguri and Strahilevitz [2021] conducted two experiments to study the effect of dark patterns. Their first experiment, an online survey with 2000 participants, showed the strong influence of mild and aggressive dark patterns. Mild dark patterns resulted in double the number of registrations compared to the control group, while aggressive dark patterns led to approximately four times as many registrations. Building on this, Luguri and Strahilevitz [2021] conducted a second experiment that surveyed around 3800 participants to investigate the efficacy of specific dark patterns. Some dark patterns like *hidden information* were highly effective and doubled the acceptance rate, whereas some dark patterns, like *scarcity condition*, showed little effect.

M. Bhoot et al. [2021] characterised dark patterns based on user's susceptibility to them

In a similar approach, M. Bhoot et al. [2021] investigated people's susceptibility to 12 dark patterns through an online questionnaire. The results for individual dark patterns showed some disparities. To expand their understanding of the result, M. Bhoot et al. [2021] characterised the dark patterns using five variables: *frequency of occurrence*, *trustworthiness*, *level of frustration*, *misleading behaviour* and *physical appearance*.

Research shows inconsistent results regarding users' awareness

There are mixed claims regarding users' awareness of dark patterns. According to Lupiáñez-Villanueva et al. [2022], the average consumer's awareness of dark patterns is low, with many accepting them as a norm. However, once a dark pattern is identified, it tends to leave a negative impression on the user. Similarly, Di Geronimo et al. [2020] claims that though most users find it difficult to identify dark patterns, they become much more adept at identi-

fying them once informed. In contrast, Bongard-Blanchy et al. [2021] state that most users are aware of the potential influence of dark patterns, but this awareness does not necessarily help them resist their influence.

Dark pattern research has expanded across cultures and age groups

Since understanding the impact of dark patterns remains a core question for future research, researchers have started to explore the influence of dark patterns on people of various age groups individually. As such, some studies have tried to understand their effect on kids [Albuquerque et al., 2024; Fitton et al., 2024; Renaud et al., 2024] and older generations [Anaraky et al., 2023; Sánchez Chamorro et al., 2024a]. Furthermore, there is a constant effort to understand the impact dark patterns have in different countries, which corroborates an understanding of dark patterns on a universal level. Some notable examples of places where research has occurred include Japan [Hidaka et al., 2023; Seaborn et al., 2024], India [M. Bhoot et al., 2021; Sharma, 2023], Germany [Krisam et al., 2021; Mildner et al., 2023], European Union (EU) [Kontogeorgou et al., 2023; Lupiáñez-Villanueva et al., 2022; Tiemessen et al., 2023], the United Kingdom (UK) [Renaud et al., 2024; Vigh et al., 2024], and the United States (US) [Chordia et al., 2023; Schaffner et al., 2022].

2.1.3 Countermeasures

Combating dark patterns has become a prominent focus for researchers

Research on mitigating the consequences of dark patterns has now started to gain momentum. Gray et al. [2024] conducted a workshop at the recently concluded CHI conference, where they emphasised fighting dark patterns. Researchers across various disciplines have unanimously called for increased awareness of dark patterns among users [Bongard-Blanchy et al., 2021; Di Geronimo et al., 2020; Lupiáñez-Villanueva et al., 2022]. Moreover, researchers have also emphasised the need to make UI designers more aware of the ethical aspects of design through appropriate education [Ahuja and Kumar, 2024; Gray et al., 2021]. Bongard-Blanchy et al. [2021] also stress teaching methods to detect dark pattern. However, Stavrakakis et al. [2021] point out that not all dark patterns can be

Not every dark patterns is detectable

identified, whether through automated or manual methods. Some dark patterns remain undetectable due to the considerable variation in their implementation.

Automatic detection of dark patterns has made substantial progress

As manual detection can be tedious for the user, advancements have been made towards the automatic detection of dark patterns. Mathur et al. [2019] introduced an automated technique that allows experts to identify text-based dark patterns on shopping websites. Their contribution marked an important milestone for subsequent detection tools, as many researchers have turned to computer vision for the detection of visual cues [Chen et al., 2023; Mansur et al., 2023]. Another approach to automatic detection employs machine learning. Soe et al. [2022] used a dataset of cookie banners from 300 news websites to train a prediction model aimed at detecting dark patterns in cookie banners.

Research involving visual countermeasures

Recently, there have been approaches to analysing the influence of visual countermeasures against dark patterns. Schäfer et al. [2023] conducted an online survey to investigate the effectiveness of six visual countermeasures against three common dark patterns: *Low-Stock Warnings*, *Confirmshaming*, and *Visual Interference*. In a follow-up work, Schäfer et al. [2024] examined the effectiveness of three visual countermeasures against 13 common dark patterns using a lab experiment that provided more profound insights into the experiences of average users. Jafari and Vassileva [2024] conducted a similar user study using a three-level warning system, as shown in Figure 2.4, to alert users about manipulative designs on a simulated app page and explored the impact of different warning levels on user behaviour. Another recent study touching on visual cues was carried out by Vigh et al. [2024], who investigated *Nudging* on websites selling alcohol with the goal of developing interventions that would reduce alcohol consumption in moderate to light alcohol consumers.

Legislature as a means to challenge dark patterns

Last but not least, Bongard-Blanchy et al. [2021] also proposed the elimination of dark patterns from digital services. There have been some ways to suggest countering dark patterns by removing dark patterns from the UIs. One proposal suggests the introduction of UI regulations through the legislature. A notable achievement in this field

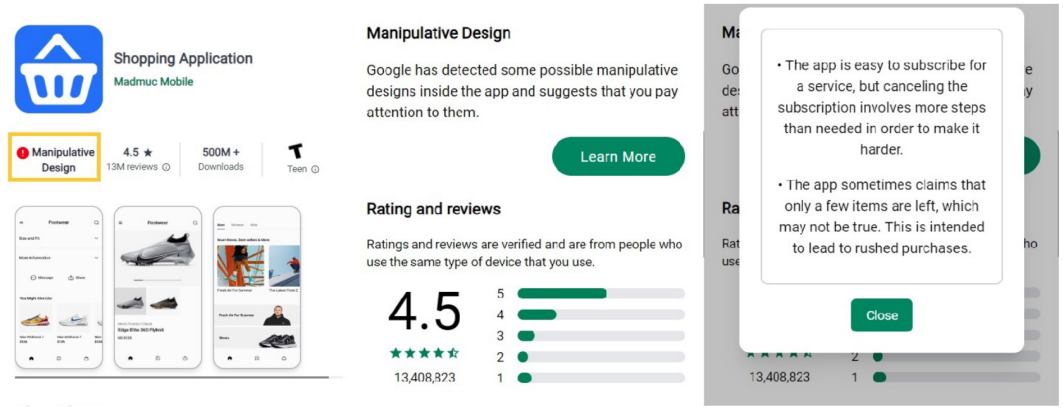

Figure 2.4: Jafari and Vassileva [2024] implemented a sequential progression of warning levels. The initial warning level is marked on the left with a red dot. When scrolling down, the users reach the second warning level, shown in the middle, which includes a brief text description. The third warning level appears when users select "Learn More" and offers an explanation for the warning.

is the introduction of the General Data Protection Regulation (GDPR), which caused the widespread use of consent banners on websites [Degeling et al., 2019]. On top of that, regulatory bodies across the world have started to address dark patterns [Gray et al., 2024].

Concepts promoting the interest of the users

Researchers have also approached the concept of bright patterns as a way to counter dark patterns. Bright patterns are conceptual antonyms to dark patterns, as bright patterns operate in the user's best interest [Grassl et al., 2020; Sandhaus, 2023]. A more neutral concept similar to bright patterns is that of fair patterns, which are designed to promote a fair interface for both the users and the companies [Potel-Saville and Francois, 2023].

2.1.4 Literature Reviews

Literature reviews have gained relevance in dark patterns

Lukoff et al. [2021] highlighted how dark pattern research is increasing exponentially in the HCI community. With the increase in contributions, tracking the evolution of the body of knowledge on dark patterns and establishing an overview becomes essential. Hence, literature reviews have gained relevance as ways to keep up with the latest re-

search in a particular domain [Snyder, 2019]. A systematic literature review follows a replicable, scientific, and transparent methodology to minimise bias in literature searches, whereas meta-analysis applies statistical techniques to aggregate findings and offer more reliability than individual studies [Tranfield et al., 2003].

Various guidelines for a systematic literature review exist

Several guidelines exist regarding systematic literature reviews. These are tailored to particular domains like health care [Khan et al., 2001], legal scholarship [Snel, 2018], or software engineering [Kitchenham and Charters, 2007]. The PRISMA guidelines were initially created with the field of medical science in mind, as it was essential for clinicians to stay up to date with the research. They were a revision of the *Quality Of Reporting of Meta-analyses* (QUOROM) statement [Moher et al., 2009]. Page et al. [2021] modified these guidelines to facilitate systematic literature reviews for a broader research field. Since then, there has been a significant increase in literature reviews following the PRISMA guidelines in the HCI community [Stefanidi et al., 2023].

Mathur et al. [2021] established the groundwork for future unified research

Mathur et al. [2021] reviewed the literature and analysed different taxonomies of dark patterns. This literature review resulted in an elaborate explanation of how researchers define dark patterns, including their types, and their attributes. Mathur et al. [2021] created a taxonomy and laid the foundation for unified future research spanning various domains.

Literature reviews conducted in the following years

Anne de Haas and Lee [2022] studied 38 papers. They underscored the lack of research addressing the potential risks of manipulation through audio design in *augmented reality* (AR) and called for increased awareness and the development of protective measures for users against these manipulative effects. Similarly, Monge Roffarello et al. [2023] evaluated 43 papers to study dark patterns that cause psychological harm and identify their attributes, exploitation methods and impact on digital wellbeing. As a result, Monge Roffarello et al. [2023] proposed the concept of *Attention Capture Dark Patterns* (ACDP) and introduced its definition and identified 11 such dark patterns. Gray et al. [2023] reviewed 79 papers that empirically examined

dark patterns, focusing on identifying their presence and impact and the user experience associated with them.

Literature reviews conducted in 2024

Chang et al. [2024] analysed 51 papers to identify critical theories in dark patterns research and called for more robust theoretical integration in future studies. Hadan et al. [2024] assessed 13 papers to review dark patterns in XR, identifying eight key manipulation strategies and proposing future research on unintentional deception, user education, and ethical design policies. Nie et al. [2024] examined 76 papers and proposed the *Dark Pattern Analysis Framework* (DPAF), which offers a comprehensive classification of dark patterns, detailing their types, user impacts, and potential applications, as well as the capabilities of detection tools.

Zielke [2024] conducted a similar literature review in the form of a bachelor's thesis

Another systematic literature review of importance in the context of this thesis was conducted by Zielke [2024]. In this review, 47 papers on dark patterns published at CHI conferences between 2010 and 2023 were taken under a microscope to track the evolution of dark pattern research in HCI. Despite having different research scopes and addressing different research gaps, our work closely aligns with the work of Zielke [2024], as both are bachelor's thesis projects conducted under the same supervision and chair at the university.

2.2 Dark Patterns Beyond HCI

Dark patterns in legislature

As dark patterns started to receive attention, the legal sector began to expand in both the research and practice of fighting against them. Brenncke [2024] gives an account of the legal response to dark patterns in the EU, while Nousiainen and Perdomo Ortega [2023] present the situation in the US. Many highly reputed companies have been called to the court of law in the past few months over their use of

dark patterns. Some prominent examples include Adobe[3] in the US and X (formerly known as Twitter)[4] in the EU.

Dark patterns in robotics

In robotics, Dula et al. [2023] explored potential dark patterns in robots integrated into social environments, such as those working in caretaking for the elderly, education for kid, or entertainment. Lacey and Caudwell [2020] suggest that the appearance of a robot could act as a potential dark pattern. For example, cuteness is designed to foster user attachment, bonding, and protective feelings, creating ideal conditions for companionship and care. Building on these findings, Lindblom et al. [2024] aimed to explore people's perceptions of privacy regarding social robots with varying appearances.

Dark patterns in gaming

Zagal et al. [2013] created a taxonomy of dark patterns in the context of gaming. Over the years, game designers have adopted dark patterns to generate interest and revenue in pay-to-win business models [Freeman et al., 2022]. Consequently, designers must be urged to implement ethical games that protect the interest of the users [Denoo et al., 2024; Hodent et al., 2024]. Among the reputed gaming companies that have faced scrutiny in the news are EA Sports, who faced backlash on the conceptualisation of their lootboxes [Pfeiffer and Wawra, 2023], and Epic Games, who were fined by the Netherlands Authority for Consumers and Markets (ACM) for dark patterns in their game Fortnite[5].

Dark patterns in extended reality

Dark patterns in XR have recently attracted massive research interest. Hadan et al. [2024] conducted a literature review and proposed future work in this domain. Krauß et al. [2024] conducted 10 co-design workshops, identifying 10 novel dark patterns and classifying four XR characteristics that heighten dark patterns in XR.

[3] https://www.techtarget.com/searchcio/news/366593576/FTC-DOJ-take-aim-at-dark-patterns-with-Adobe-lawsuit [Accessed: September 2024]

[4] https://apnews.com/article/x-twitter-european-union-musk-dsa-645e9a224cd82ed1bc3cde9156215293 [Accessed: September 2024]

[5] https://gamerant.com/epic-games-fortnite-fined-why/ [Accessed: September 2024]

Chapter 3

Meta-Analysis

The following chapter focuses on the methodology and findings of the literature review. The review was conducted in accordance with the PRISMA statement guidelines [Page et al., 2021]. The methodology, including specific details on data collection and screening methods, will be thoroughly explained. Subsequently, the results of the review will be presented.

3.1 Methodology

We followed the PRISMA guidelines to conduct the literature review

For our systematic literature review, we adhered to the guidelines set by the PRISMA statement [Page et al., 2021] because this method offers a structured approach for conducting and reporting systematic reviews. In the field of HCI, Stefanidi et al. [2023] observed a substantial rise in the use of PRISMA guidelines since their modifications in 2020. This trend is also reflected in the examples listed in Chapter 2.1.4 - six out of eight literature reviews on dark patterns employed the PRISMA guidelines in some capacity, with [Mathur et al., 2019] and [Nie et al., 2024] being the only exceptions. Following the approach of Zielke [2024], we developed a *codebook* to assist with the content analysis and categorise the literature contributions in our meta-analysis.

We provide an overview of current research directions on dark patterns

As research on dark patterns rapidly expands across various study spectra, it becomes essential to establish a comprehensive overview of current research trajectories. This thesis aims to offer such an overview, with a particular focus on studies dealing with the influence and impact of dark patterns on users. This work seeks to highlight the current state of research devoted to introducing and enhancing countermeasures against dark patterns.

We limited our scope to research papers published from 2020 onwards

Considering the scope of this bachelor's thesis and the limited resources available, it was crucial to define the boundaries of our literature review to ensure a qualitative assessment of the research questions outlined in Chapter 1. Hence, this review focuses on literature published in conferences or journals since 2020. This decision was also partially influenced by Gray et al. [2024], who observed a growing momentum in recent years toward identifying problematic practices and finding ways to prevent or discourage dark patterns.

The following sections will discuss our process for identifying literature, screening it, and making an eligibility assessment. Additionally, the 27-item PRISMA checklist and the 12-item PRISMA Abstract checklist are provided in Appendix D.

3.1.1 Identification and Screening of Literature

We conducted a literature search in the ACM Digital Library and IEEE Xplore

The first step in our systematic literature review involved the collection of the dataset. To accomplish this, we conducted an initial search using the *Association for Computing Machinery* (ACM) Digital Library[1]. We selected the ACM Digital Library as our primary source, as it is well-recognised for hosting high-quality research papers on HCI. To ensure a broader scope, we also utilised the *Institute of Electrical and Electronics Engineers* (IEEE) Xplore Digital Library[2], which covers a wide range of technical disciplines. By employing both platforms, we sought to capture

[1] `https://dl.acm.org/` [Accessed: August 2024]

[2] `https://ieeexplore.ieee.org/Xplore/home.jsp` [Accessed: August 2024]

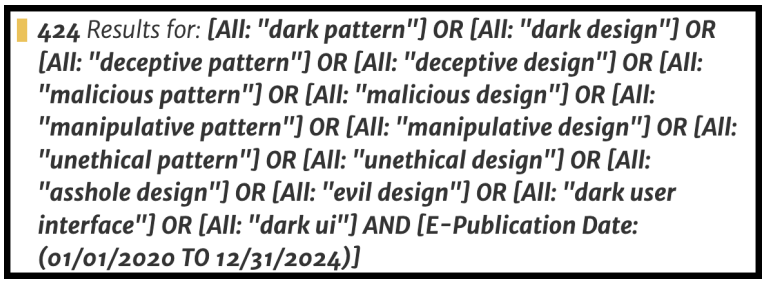

Figure 3.1: The search query used to identify relevant literature. Although this screenshot was captured in October 2024, the actual literature search was conducted in August 2024. During the search, 413 results were returned for our query.

a diverse set of perspectives, thus ensuring a comprehensive overview of trends and developments across multiple domains.

The set of keywords was selected based on established literature reviews

It was crucial to identify the appropriate keywords necessary for locating relevant literature across both databases. To accomplish this, we reviewed existing systematic reviews on dark patterns to identify common keywords used in the field. Our final set of keywords was formed by compiling the union of keywords from several literature reviews [Chang et al., 2024; Gray et al., 2023; Zielke, 2024]. Figure 3.1 illustrates the search query used to retrieve relevant literature. The keywords were enclosed in quotation marks to ensure they exactly matched the search terms and were separated by the Boolean operator OR. The literature search was conducted between 10 and 25 August 2024. After the search, 413 results were retrieved from the ACM Digital Library and 26 results were retrieved from IEEE Xplore.

We carried out the identification and screening of literature twice, but concurrently

During our initial examination of the search results, we found that many of the retrieved papers were not relevant to our focus. Therefore, it was necessary to screen the corpus of the dataset concurrently while identifying the literature. Although this approach did not align with the ideal methods outlined in the PRISMA guidelines, we deemed it sensible, as it would filter out research papers that were less

pertinent to our study, ensuring that those included in the corpus contributed meaningfully to dark pattern research. Additionally, we repeated the identification and screening process two weeks after the initial review to allow for a small incubation effect since studies have indicated that performing the same action after a period can provide a fresh perspective [Sio and Ormerod, 2009].

The screening criteria were aligned with those established by Gray et al. [2023]

Defining the screening criteria for our process was essential. To this end, we aligned our criteria with those established by Gray et al. [2023], making slight modifications to ensure that our dataset met our specific needs without exceeding the resources available for a bachelor's thesis. In order for a record to be included in the corpus, all of the following criteria had to apply:

1. the record had to be written in English;
2. the record had to mention "dark pattern" or one of the other keywords as mentioned in Figure 3.1 in either the title, abstract or paper keywords; and
3. the record had to be published in a journal, conference proceedings, government technical report, or similar archival venue.

Examples of literature excluded after the screening procedure.

We excluded contributions that did not meet these criteria. First, we removed papers not written in English, such as [Frejus et al., 2023]. Second, we eliminated papers that, while relevant to the topic of manipulation, did not align with our focus. For instance, Bellini [2023] explored deceptive financial strategies in cases of domestic violence, and Asif et al. [2024] addressed rising security concerns in unmanned aerial vehicles. Although valuable in their respective fields, these studies were not pertinent to our review. Finally, we excluded contributions such as [Gray et al., 2024], which did not meet our screening criteria despite extensively featuring dark patterns. Additionally, we removed proceedings reports from various conferences such as CHI [2024].

Following this, we eliminated duplicate papers identified during this phase of the literature search. For instance,

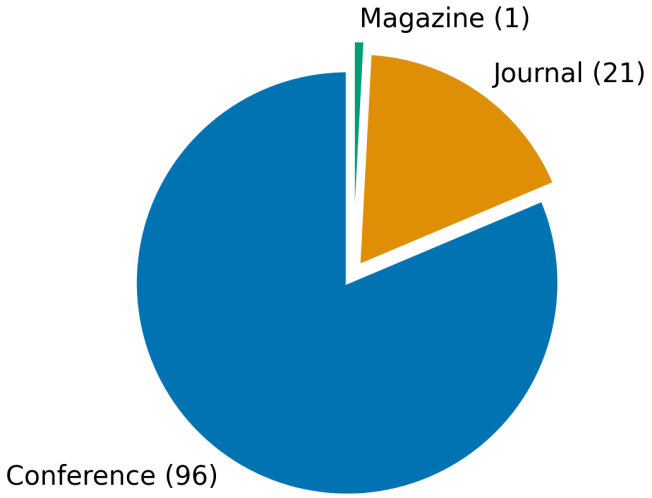

Figure 3.2: The distribution of publishing venues for the papers collected during the identification.

Narayanan et al. [2020] was published in two venues in 2020 - Queue (Volume 18, Issue 2) and Communications of the ACM (Volume 63, Issue 9). Three other papers, including Mansur et al. [2023] and Mansur [2023], were found in both the ACM Digital Library and IEEE Xplore. Ultimately, we retained 114 literature contributions.

Duplicates identified after the screening phase were removed

Given that the research community has only recently shifted its focus towards countermeasures to thwart dark patterns, we aimed to broaden our search in this area. To do this, we manually screened the papers to identify any technical countermeasures the search engines may have overlooked. This process led to the discovery of four additional research papers, which were subsequently added to our dataset.

References were screened for literature focused on DP countermeasures

Ultimately, our dataset after the screening procedure comprised 118 papers, with 96 published in conference proceedings, 21 in journals, and one in a magazine, as illustrated in Figure 3.2. Of these 118 papers, 104 were retrieved from the ACM Digital Library, 10 from IEEE Xplore, and four from references. Figure 3.3 provides a graphical repre-

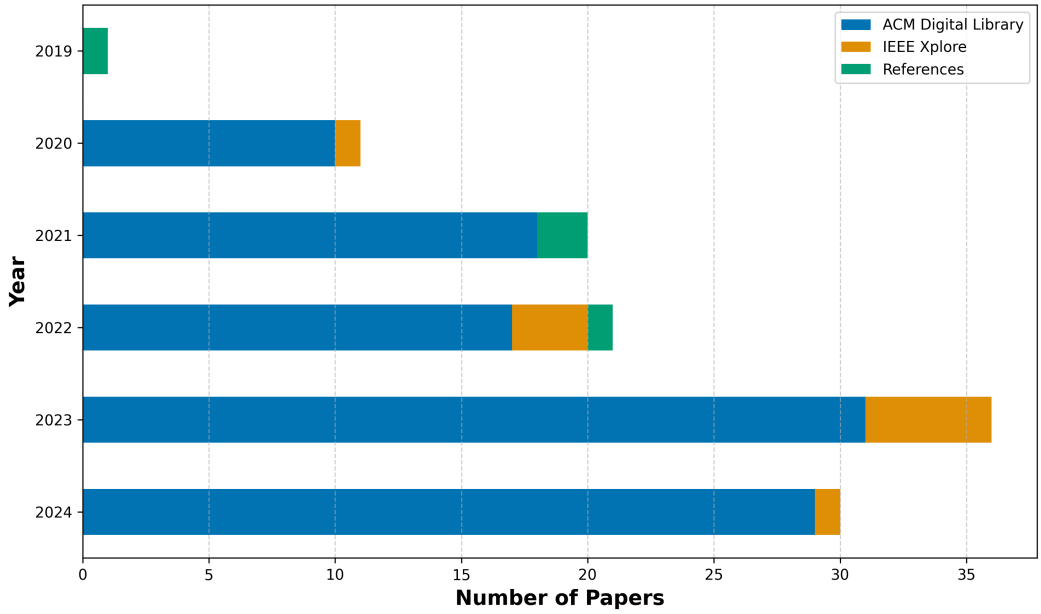

Figure 3.3: The distribution of the papers collected during the identification process is displayed, with the papers organised by year and colour-coded to indicate the sources where they were retrieved.

sentation of the papers sorted by source and year of publication.

3.1.2 Eligibility Evaluation of Literature

The eligibility criteria needed to be appropriately defined to address our research questions

Before the eligibility assessment, our dataset consisted of 118 records, each of which made a valuable contribution to dark patterns research. However, given the limitations of a bachelor's thesis, it proved challenging to assess and review all the records in their entirety. Moreover, to enhance the quality of our assessment and the answers to our research questions, it was prudent to divide our corpus into various study themes.

Therefore, we coded our dataset into seven thematic categories and assigned each record according to its most prominent theme. Each record was classified under a single theme only. The themes were as follows:

- SHA contains records focused on developing a shared language for dark patterns. These records may introduce new taxonomies, frameworks, or theories related to dark patterns or identify new dark patterns in UI.
- IMP contains records that examine the impact of dark patterns on users. These records may investigate how users perceive dark patterns or how they respond to them.
- ETH contains records that explore dark patterns from an ethical standpoint. These records primarily provide ethical guidelines for designers or discuss the fairness aspect of UI design.
- LAW contains records that highlight legislative developments related to dark patterns. These papers examined the effects of laws such as the GDPR.
- COU contains records that investigate the development of technical countermeasures against dark patterns and their impact on users. This category includes tools designed to counter dark patterns and experiments with users interacting with these countermeasures.
- TRD contains records that analysed dark patterns in relation to other domains, such as robotics, XR and CUI, thereby representing a trending area for transdisciplinary research.
- OTH contains records that included workshop papers, panel papers, *special interest group* (SIG) papers, dissertations, or personal opinions from authors on dark patterns

We categorised each contribution into one of the seven identified themes—SHA, IMP, ETH, LAW, COU, TRD, and OTH—according to their most prominent focus

Figure 3.4 gives a graphical overview of the distribution of papers across these themes. We included records classified under IMP and COU in our literature review. Additionally, we incorporated contributions made in 2024 and categorised under SHA. We also included [Mathur et al., 2021], as this paper represents one of the first efforts to establish a shared language across various disciplines and lays groundwork for future researchers to build upon.

Eligibility criteria for our literature corpus

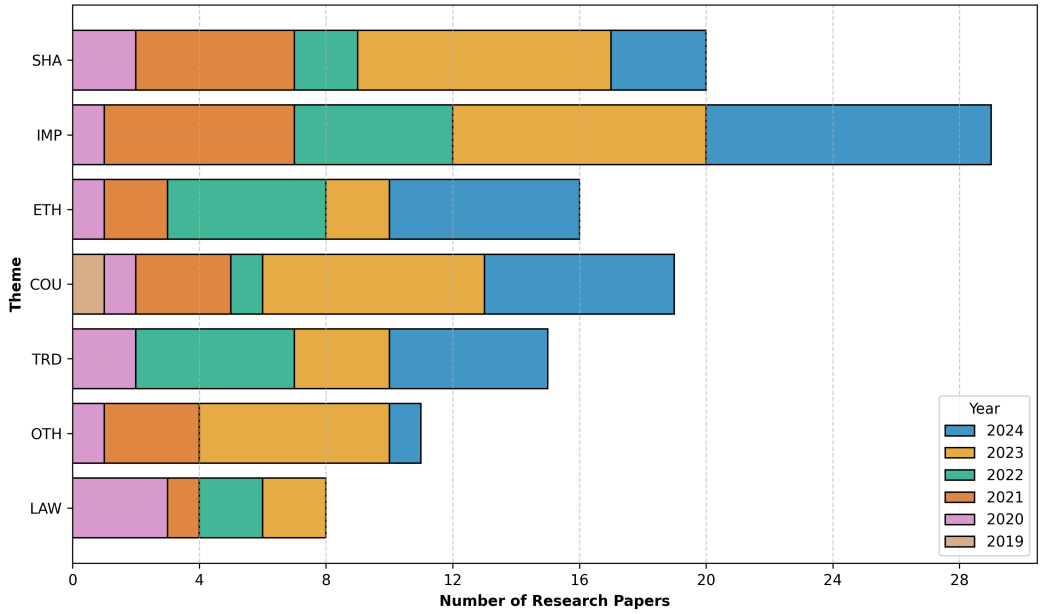

Figure 3.4: The research papers were categorised into seven themes. This figure illustrates this distribution and the papers' years of publication.

Drawbacks of our approach

We acknowledge that this approach has a significant drawback. One record may belong and provide valuable and unique insights related to multiple themes. However, to align with our research questions, we categorised papers that highlighted different themes but included either `IMP` or `COU` elements under those themes. This decision was made to enhance the diversity of our literature review.

Our final corpus comprised of 52 records

By the conclusion of the eligibility assessment, our corpus comprised 52 records. Detailed assessment of each individual record can be found in Appendix A. Furthermore, Figure 3.5 illustrates the PRISMA flow chart, summarising our corpus collection process.

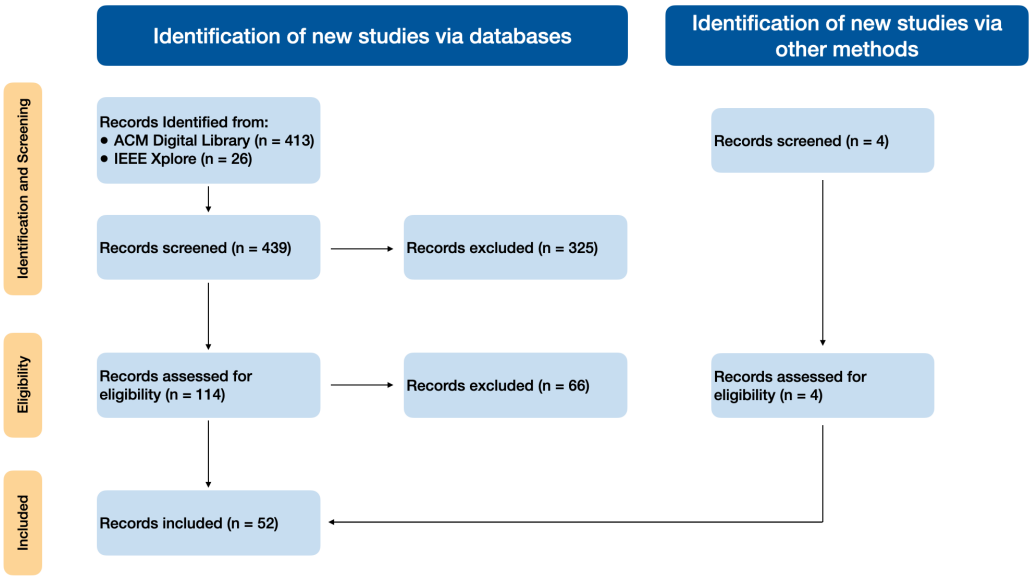

Figure 3.5: The PRISMA flow chart offers an overview of our corpus collection process. We have adapted this flow chart to reflect the specific methodology we employed. The screening and identification of literature were conducted concurrently.

3.1.3 Analysis

We used a codebook for our meta-analysis, following Gray et al. [2023] and Zielke [2024]

In our next research step, we aimed to establish a solid foundation for the meta-analysis of our literature corpus. To achieve this, we followed the approach of Gray et al. [2023] and Zielke [2024], who employed the inductive qualitative content analysis method [Hsieh and Shannon, 2005]. Additionally, we formulated key questions to gain a deeper understanding of our corpus.

For the meta-analysis, we focused on four aspects to address our research questions

Our first key question aimed to determine the type of contribution each record made within the context of HCI and the specific aspect of dark pattern research it focused on. The second key question sought to understand the "how" and "what" of the research methodology - how the researchers conducted their studies and on which platforms they reported about. The third key question aimed to assess the extent to which different types of dark patterns have been researched. Lastly, we aimed to examine the degree

to which the research community is addressing the harms that dark patterns inflict on users.

These questions helped us identify several trends in dark pattern research in recent years (RQ1) and predict future developments (RQ4). Furthermore, they allowed us to observe the impacts of dark patterns on users (RQ2) and explore efforts to mitigate the effects of dark patterns (RQ3). Moreover, this approach enabled us to identify research gaps within the broader context of the field.

Our codebook comprised seven broad and distinct categories

We identified seven categories for our codebook. To maintain consistency, we aligned our codebook with notable research contributions in the field, which will be explained subsequently. The dataset was reviewed and coded three times to ensure high quality and accuracy in the coding. If a paper did not fit a particular code within a specific category, we chose not to assign it a code. Additionally, a paper could be assigned multiple codes within a single category. An overview of the codebook is provided in Appendix C.

Contribution Types

Research papers were classified according to their contribution types as outlined by Wobbrock and Kientz [2016]

Categorising research papers by contribution types allows for a more precise evaluation during the review process. We adopted the seven HCI contribution types proposed by Wobbrock and Kientz [2016]. This categorisation was chosen because it provides a comprehensive and systematic framework for understanding the diverse ways in which researchers can contribute to the field of HCI. The various contribution types are as follows.

- `Empirical` research that presents new findings based on systematic observations, experiments, or user studies. For example, these studies may explore how individuals interact with dark patterns or how they identify such patterns.

- `Artifact`[3] research that introduces novel systems, tools, or techniques. These studies might, for instance, propose new tools to negate the effects of dark patterns.
- `Methodological` research that offers new approaches to conducting research, including new designs for experiments, analysis or evaluation. Such studies might, for example, introduce taxonomies for dark pattern research.
- `Theoretical` research that enhances conceptual understandings. Specifically, it aims to explain why people behave in certain ways. For instance, these studies might develop theories about how vulnerable groups perceive dark patterns.
- `Dataset` research focuses on the creation and sharing of new datasets, which can be used by other researchers for further studies. An example would be sharing a dataset of websites containing dark patterns to be used in the testing of new detection tools.
- `Survey` research reviews and synthesises studies within a specific field to offer an overview of the current state of research.
- `Opinion` research expresses the opinion of an author on a particular topic. The author is usually an experienced researcher whose arguments tend to influence the reader's perspective.

Research papers were coded as `Empirical`, `Artifact`, `Methodological`, `Theoretical`, `Dataset`, `Survey`, and/or `Opinion`

Research Methods

We further categorised the selected research papers based on their respective research methods. After an initial examination of our dataset, we determined it was most appropriate to adopt the empirical research methods outlined by Mathur et al. [2021]. Additionally, we included the literature review as a research method, as many studies relied

Research methods were coded according to the methods identified by Mathur et al. [2021]

[3] Although the thesis is written in British English, we use the American English spelling for "artifact," as defined by Wobbrock and Kientz [2016].

on analysing existing research. Ultimately, we identified the following research methods:

Research papers were coded as `Field Study`, `Focus Group`, `Interview`, `Lab Study`, `Literature Review`, and/or `Questionnaire`

- `Field Study` involves collecting data in a natural, real-world setting that allows the researcher to gain insights into the real-world reactions of participants. We also included the testing of countermeasure tools with the help of a dataset in this category.
- `Focus Group` involves collecting data in small group researcher-led discussions on a particular topic. We also included researcher-led workshops in this category.
- `Interview` involves collecting data in a one-on-one setting using open-ended questions.
- `Lab Study` involves collecting data in a controlled laboratory environment that allows the researcher to manipulate the variables.
- `Literature Review` involves collecting data through a comprehensive review and synthesis of existing research.
- `Questionnaire`[4] involves collecting data from a large group of participants with the help of a structured set of questions that is often administered online.

Dark Pattern Types

We utilised the high-level dark patterns defined by Gray et al. [2024] as our coding framework

For our analysis, it was critical to identify the types of dark patterns being researched in the literature. Thus, we followed the approach of Gray et al. [2024] and used the high-level dark patterns as viable categories. We opted for this categorisation as it provided a more manageable framework for analysis, given the limited size of our corpus. Analysing the dataset based on meso-level or low-level patterns could have resulted in overcategorisation,

[4] Although Mathur et al. [2021] define the research method as "Survey", to prevent confusion with the contribution type `Survey`, we use the term "`Questionnaire`".

which would have compromised the clarity of our findings. At the same time, we recognise the potential risks of under-categorisation and acknowledge the limitations that come with it.

- `Forced Action` describes dark patterns that compel users, either consciously or unconsciously, to take additional actions, thereby preventing them from proceeding with their originally intended tasks. Examples of this include nagging tactics, as illustrated in Figure 2.1.
- `Interface Interference` describes dark patterns that manipulate UIs to favour actions that are detrimental to the user. For instance, this can involve visually emphasising the more expensive option between two products.
- `Obstruction` describes dark patterns that impede the user's workflow, actively hindering the action the user intends to perform. An example is the "Roach Motel" pattern, as shown in Figure 2.2.
- `Sneaking` describes dark patterns that obscure or withhold information from users, which, if revealed, would likely lead users to reject the action. An example of this is the covert addition of items to a shopping basket.
- `Social Engineering` describes dark patterns designed to exploit users' social psychology. An example is falsely indicating that a product is highly popular, as depicted in Figure 2.1.

Research papers were coded as `Forced Action`, `Interface Interference`, `Obstruction`, `Sneaking`, and/or `Social Engineering`

In our corpus, we identified five cases where new types of dark patterns, not yet covered by the ontology of Gray et al. [2024], were introduced. We matched these new dark patterns to the closest corresponding high-level dark pattern category. This finding highlights the continuous expansion of dark pattern research, with new patterns emerging as different domains explore this field. Table 3.6 presents the mapping of dark pattern types for each record that introduced a new pattern and did not classify it under the ontology of Gray et al. [2024].

New dark patterns were coded to their closest fitting dark pattern type

Reference	Dark Pattern Type	New Identified Dark Pattern
Chaudhary et al. [2022]	`Forced Action`	Attention Quicksand, Extreme Countdown
	`Interface Interference`	Feature Fog, Switch-Off Delay
	`Social Engineering`	Bias Grid
Dubiel et al. [2024]	`Interface Interference`	Synthetic Voice
King et al. [2023]	`Forced Action`	Narrative Obligation
	`Interface Interference`	Default to Purchase, Emotional Interpersonal Persuasion, Physical Placement, UI Misdirection
	`Obstruction`	Predatory Monetization
Kontogeorgou et al. [2023]	`Interface Interference`	Muscle Memory
Wu et al. [2023]	`Forced Action`	Forced Endorsement, Forced Wholesale
	`Sneaking`	Fuzzy Targeting
	`Social Engineering`	Disgracing Others, Egoistic Norms, Playacting, Retaining Customers, Sophistry

Table 3.6: Coding of newly introduced dark patterns in five records that did not classify the dark patterns according to the ontology by Gray et al. [2024].

Study Focus

Categorisation based on contributions to dark pattern research

We also aimed to categorise the papers based on the specific aspects of dark pattern research they focused on. These categories were developed following an initial examination of the dataset, and the records were coded accordingly.

- `Countermeasure Impact` describes research papers that examine how users perceive and respond to countermeasures designed to mitigate dark patterns.
- `Countermeasure Interpretation` describes research papers that explore how countermeasures can be im-

proved, how they are utilised, and that generally deepen our understanding of countermeasure effectiveness.

- `Countermeasure Proposal` describes research papers that introduce new techniques or tools to counteract dark patterns.
- `DP Discovery` describes research papers that identify previously unrecognised dark patterns, often in the context of emerging user interfaces.
- `DP Impact` describes research papers that investigate the effects of dark patterns on users.
- `DP Interpretation` describes research papers that expand our understanding of dark patterns and their implications.
- `DP Susceptibility` describes research papers that explore how detectable dark patterns are and how users might recognise them.
- `Taxonomy Construction` describes research papers that introduce new taxonomies or classifications for dark patterns.

Research papers were coded as `Countermeasure Impact`, `Countermeasure Interpretation`, `Countermeasure Proposal`, `DP Discovery`, `DP Impact`, `DP Interpretation`, `DP Susceptibility` and/or `Taxonomy Construction`

Addressed Harms

We also sought to investigate how the research community has examined the impacts of dark patterns on users. To achieve this, it was necessary to categorise the harms addressed by the papers. We had two viable options for this categorisation: the first option was to align with the normative perspective presented by Mathur et al. [2021], while the second option was based on the harms to users defined by the OECD [2022]. Ultimately, we opted for the latter, as these harms were defined on the principles of Mathur et al. [2021] but also integrated insights from other researchers, including Susser et al. [2018].

We employed the user harms defined by the OECD [2022] to categorise the research papers

- `User Autonomy` describes research papers that explore impacts on users' abilities to make independent choices.
- `Financial Loss` describes research papers that delve into the negative financial impacts experienced by users.
- `Privacy Breach` describes research papers that examine the unauthorised disclosure of user information.
- `Psychological Detriment and Time Loss` describes research papers that explore cognitive burdens or the unintended extra time users spend completing tasks.
- `Weaker or Distorted Competition` describes research papers that investigate how dark patterns undermine fair competition.
- `Reduced Consumer Trust and Engagement` describes research papers that examine the declines in users' trust in and engagement with a company due to its use of dark patterns.

Research papers were coded as `User Autonomy`, `Financial Loss`, `Privacy Breach`, `Psychological Detriment and Time Loss`, `Weaker or Distorted Competition` and/or `Reduced Consumer Trust and Engagement`

Platforms

Platforms refer to the contexts in which the dark patterns were examined

We also aimed to categorise the contexts in which researchers investigated dark patterns. Given that dark patterns are prevalent across a range of user interfaces, we deemed it essential to document these contexts, as they could offer valuable insights into emerging trends in the research.

- `E-Commerce` describes research papers examining dark patterns within the context of online shopping platforms.
- `Entertainment` describes research papers exploring dark patterns in entertainment services.
- `Gaming` describes research papers investigating dark patterns in gaming services.

Research papers were coded as `E-Commerce`, `Entertainment`, `Gaming`, `Generic`, `Navigation`, `Safety Technology` and/or `Social Media`

- `Generic` describes research papers that investigate dark patterns without focusing on a specific domain or service.
- `Navigation` describes research papers analysing dark patterns in services that provide geographic data and directions to users.
- `Safety Technology` describes research papers investigating dark patterns within services related to user safety technologies.
- `Social Media` describes research papers focused on dark patterns within social networking platforms.

Country

Broader category aimed at gaining a global perspective on dark pattern research

Lastly, we sought to examine the trends in dark patterns research across different cultures. To achieve this, we decided to document the country of focus for each study. We considered this an important step in identifying trends and understanding how research could be expanded across various cultural contexts. We labelled papers that did not clearly state the origin of participants in empirical studies or where the country of focus could not be determined as `Not Specific`.

3.2 Results

General information of literature corpus

Our dataset comprised 52 records, with 41 papers published in conference proceedings. Of these, 14 were either published at the CHI or in CHI extended abstracts. The remainder were journal articles, predominantly featured in editions of the *Proceedings of the ACM on Human-Computer Interaction* (PACMHCI). Most of the papers were sourced from the ACM Digital Library, with two records obtained from the IEEE Xplore library and four identified through references. For the analysis, we utilised *Microsoft Excel*[5] for

[5] https://www.microsoft.com/en-us/microsoft-365/excel [Accessed: September 2024]

coding, in combination with *Python*[6] to compute distribution and frequency matrices. These matrices illustrate the frequency with which each dark pattern type cooccurs with codes from other categories in the corpus of 52 literature contributions.

The following subsections present the results of our coding process and qualitative analysis. A detailed overview of the coding for each paper is provided in Appendix B.

Dark Pattern Types

42 records were coded with at least one type of dark pattern

In our corpus of 52 literature contributions, we identified 42 papers that directly addressed at least one type of dark pattern. These references often emerged from the use of dark patterns in user studies. In 32 instances (62%), a single research paper examined multiple high-level dark patterns. A more detailed explanation of the five dark pattern types, `Forced Action`, `Interface Interference`, `Obstruction`, `Sneaking` and `Social Engineering` - can be found in Section 3.1.3.

`Interface Interference` was the most common, while `Obstruction` was the least frequent dark pattern type

The most frequently studied dark pattern was `Interface Interference`, which appeared in almost 78% of the papers that addressed dark patterns. Both `Forced Action` and `Social Engineering` were equally prominent, featuring in 69% and 64% of the papers, respectively. In contrast, `Obstruction` was the least mentioned, appearing in only 48% of the papers. Figure 3.7 visually depicts the frequency of each dark pattern type, with colour coding used to indicate the number of papers mentioning each pattern in a given year.

`Forced Action` frequently co-occurred with other types of dark pattern in most instances

We also observed several instances where multiple dark pattern types were mentioned together in the same paper. As such, we investigated which dark pattern types co-occurred most frequently. Our findings revealed that `Forced Action` frequently appeared alongside both `Interface Interference` and `Social Engineering`, co-occurring with each in 57% of the papers that referred

[6] https://www.python.org/ [Accessed: September 2024]

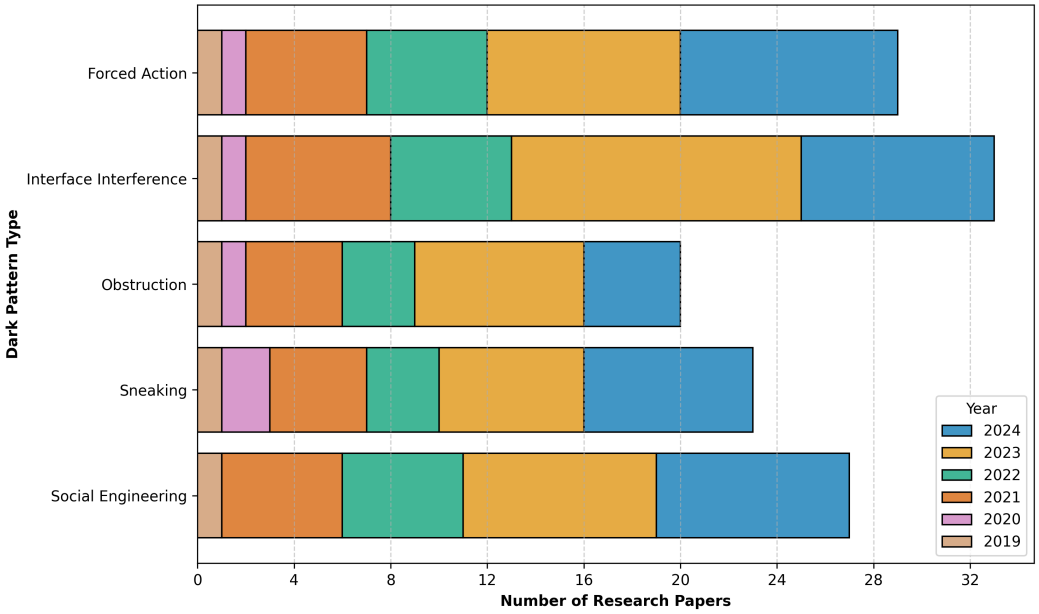

Figure 3.7: This histogram represents the prevalence of dark pattern types coded in 42 papers within the corpus, highlighting the number of papers categorising each dark pattern type by year of publication.

to a dark pattern type. Furthermore, the combinations of `Forced Action` and `Social Engineering` with either `Interface Interference` or `Sneaking` were noted as having the same number of instances as `Obstruction` (n=20), making these the most common triads of co-occurring codes. Figure 3.8 illustrates the combinations of co-occurrences that were as frequent as or more frequent than `Obstruction`.

A Frequency matrix describes the co-occurrence of two dark pattern types in our corpus.

To further analyse these co-occurrences, we computed a frequency matrix that reflected how often each dark pattern type was studied in conjunction with another. Figure 3.9 visualises these relationships as a heatmap. The diagonal values represent the overall frequency with which each dark pattern was examined. Interestingly, `Forced Action` frequently co-appeared with `Interface Interference` and `Social Engineering`, appearing together in 46% of the 52 papers.

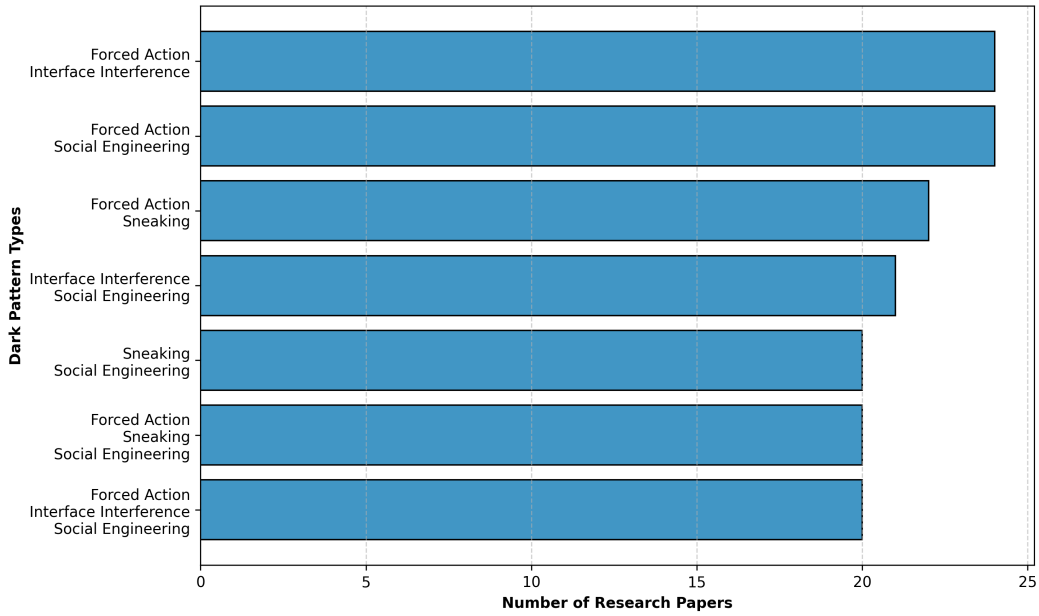

Figure 3.8: This histogram illustrates the combinations of dark pattern types coded as most frequently co-occurring in the literature corpus.

Figure 3.9: The heatmap illustrates the frequency matrix representing the co-occurrence of each dark pattern type with another within the corpus.

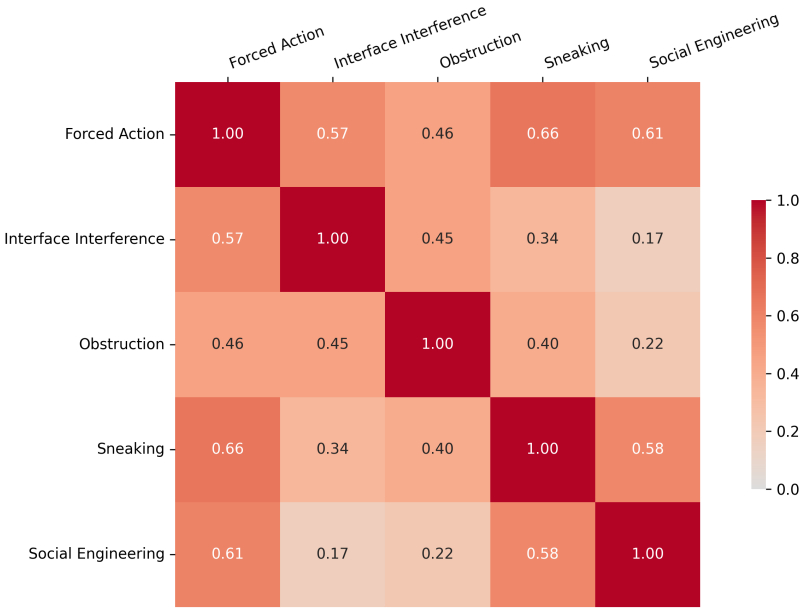

Figure 3.10: The heatmap illustrates the Pearson correlation coefficient matrix between dark pattern types.

Assuming a potential linear relationship between the codes, we measured the strength of their correlations using the Pearson correlation coefficient. Figure 3.10 presents the resulting correlation matrix. The strength of these correlations varied greatly across different dark pattern types. For example, `Forced Action`, `Sneaking`, and `Social Engineering` exhibited very strong correlations with one another, whereas the correlation between `Interface Interference` and `Social Engineering` was noticeably weaker, ultimately indicating the lower likelihood that dark patterns might be studied together in a given context.

A correlational matrix describes the Pearson correlation coefficients between the dark pattern types

Contribution Types

All of the papers in our dataset of 52 research contributions were assigned at least one code representing their contribution types. These codes — `Empirical`, `Artifact`, `Methodological`, `Theoretical`, `Dataset`, `Survey`

All records were coded with at least one contribution type

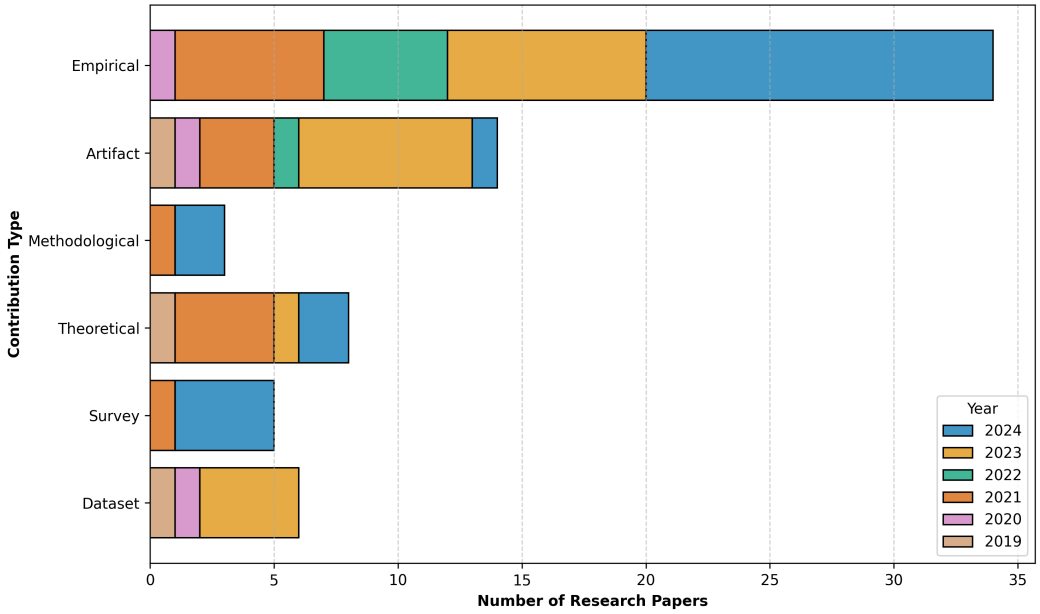

Figure 3.11: This histogram represents the prevalences of the contribution types coded in the corpus, highlighting the number of papers categorising each contribution type by year of publication.

and `Opinion`—were derived from the contributions of Wobbrock and Kientz [2016] and are explained in Section 3.1.3.

Most of our records were classified as `Empirical` contributions

Our corpus predominantly comprised `Empirical` contributions, which accounted for 65% of the papers. Additionally, we observed that 27% of the contributions were classified as `Artifact`. Other contribution types included `Methodological` (n=3), `Theoretical` (n=8), `Dataset` (n=6), and `Survey` (n=5). Notably, we did not identify any research papers that could be classified as `Opinion` contributions. Figure 3.11 illustrates the distribution of contribution types in our corpus. While we could not identify any specific combinations of contribution types that co-occurred in the corpus, it is noteworthy that out of the six instances of `Dataset` contributions, five were also coded as `Artifact` contributions.

Figure 3.12 presents the frequency of the different contribution types across the various dark pattern types in the literature corpus. The frequency matrix underscores the

Figure 3.12: The heatmap illustrates the frequency matrix representing the co-occurrence of each dark pattern type with each contribution type within the corpus.

A frequency matrix describes the co-occurrence of dark pattern and contribution types

notable presence of `Empirical` contributions. This contribution type was frequently coded alongside different dark pattern types, from being coded with `Obstruction` type in 23% of the corpus papers to being coded with the `Interface Interference` type 48% of the corpus papers. `Interface Interference` paired with `Empirical` contributions accounted for the largest number of papers. In contrast, `Artifact` contributions showed a more limited range, being coded with dark pattern types in 15% to 17% of the cases.

Research Methods

48 records were coded with at least one research method

We identified six distinct research methods— `Field Study`, `Focus Group`, `Interview`, `Lab Study`, `Literature Review`, and `Questionnaire`—across 48 research papers in our dataset. One paper, which did not utilise a specific research method, presented preliminary findings, while two others introduced detection tools. Additionally, one paper was a

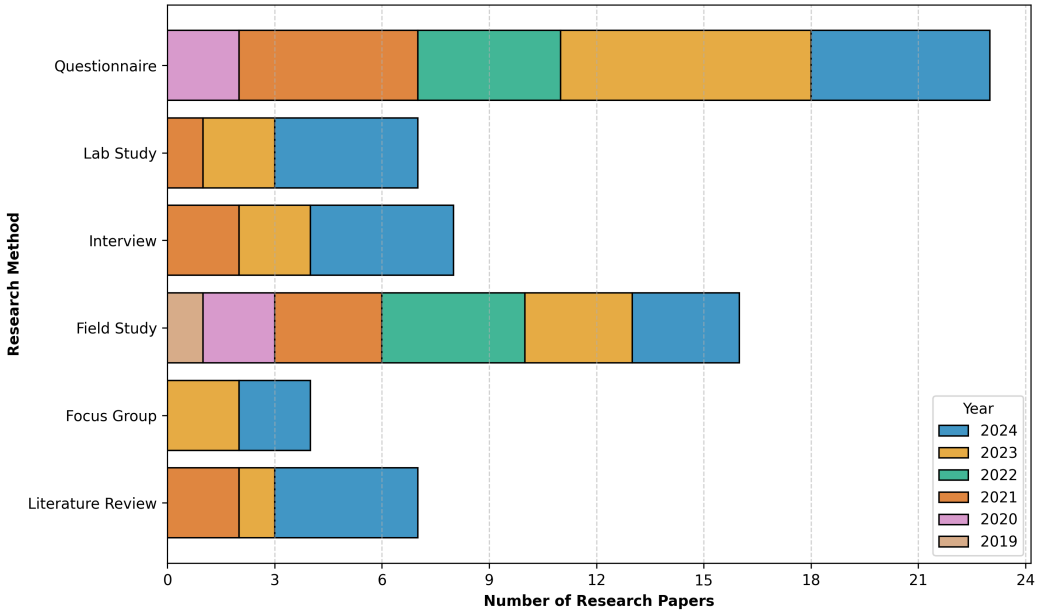

Figure 3.13: This histogram represents the prevalence of research methods coded in 48 papers within the corpus, highlighting the number of papers utilising each research method and sorted by publication year.

`Methodological` contribution, offering an evaluation technique for countermeasures. The research methods are explained in Section 3.1.3.

`Questionnaire` was the most common research method

The most common research method employed in our corpus was the `Questionnaire`, which was utilised in nearly half of the cases, specifically 48%. `Field Study` was the second most preferred method and was chosen in one-third of the instances. The `Focus Group` method has gained traction since 2023, emerging as a viable research method. Figure 3.13 illustrates the distribution of research papers categorised by various research methods and sorted by their years of publications.

`Survey` and `Interface Interference` appeared together in 33% of our corpus.

The frequency matrix depicted in Figure 3.14 illustrates the co-occurrence of each research method alongside specific dark patterns within our literature corpus. The combination of `Survey` and `Interface Interference` was the most frequently observed, appearing in 33% of the papers in our corpus.

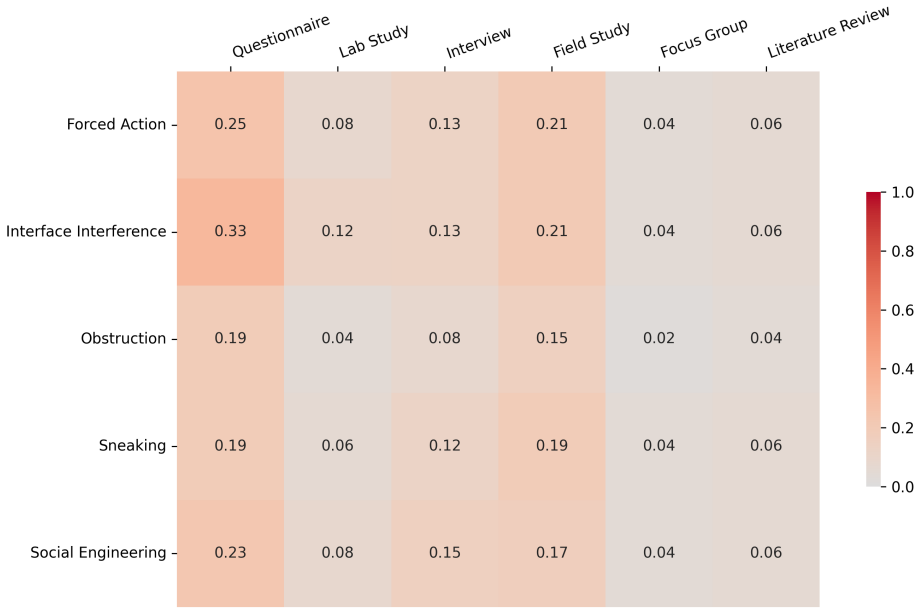

Figure 3.14: This heatmap illustrates the frequency matrix representing the co-occurrence of each dark pattern type with each research method within the corpus.

Study Focus

The eight distinct study focus categories, detailed in Section 3.1.3, served to classify the primary objectives of the collected research papers and their contributions within the context of dark patterns research. We were able to assign a code to every paper in our corpus.

All records were coded with at least one study focus

Figure 3.15 highlights that the most prevalent study focus was `DP Impact` (n=26), which appeared in approximately half of the cases. This was followed by `Countermeasure Proposal` and `DP Susceptibility`, which were present in around 30% of the total research papers. Additionally, `DP Discovery` was coded in 13% of the cases. Notably, the combination of `DP Impact` and `DP Susceptibility` was the most frequently observed co-occurrence, featuring together in roughly 20% of the cases. The frequency matrix in Figure 3.16 further supports this trend, indicating that 38% of the papers coded with `DP Impact` also included the dark pattern `Interface Interference`, while 33% were associated with the dark pattern `Social Engineering`.

`DP Impact` was the most common study focus and often appeared alongside `DP Susceptibility`

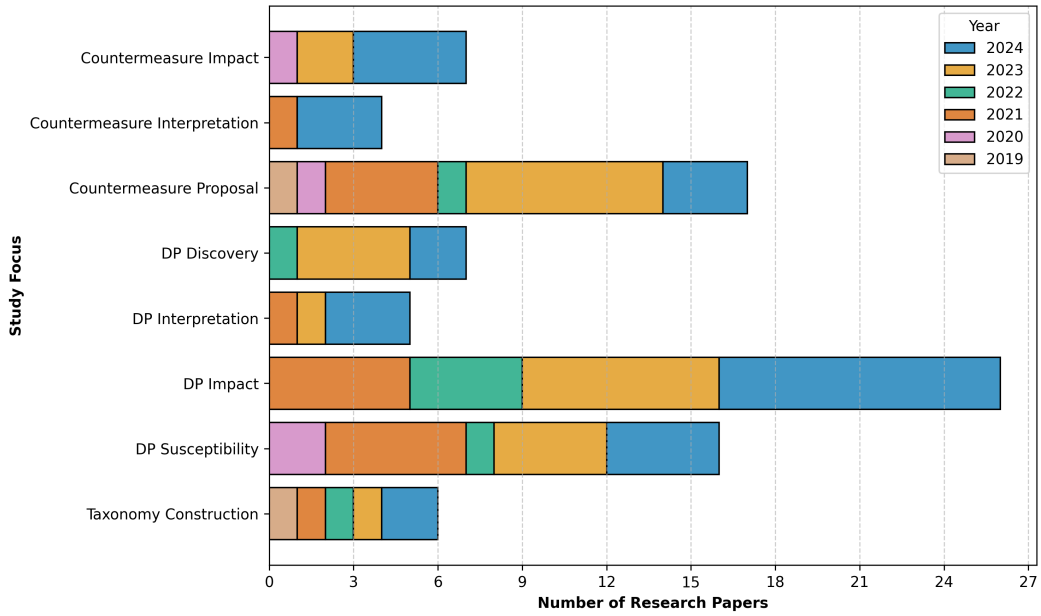

Figure 3.15: This histogram represents the prevalence of study focus areas coded in the corpus, highlighting the number of papers categorising each study focus sorted by year of publication.

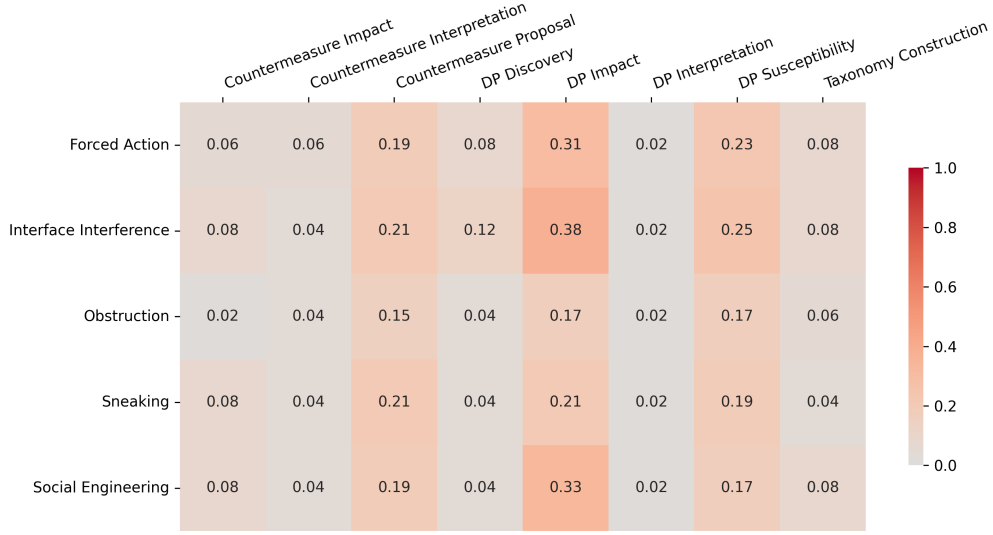

Figure 3.16: This heatmap illustrates the frequency matrix representing the co-occurrence of each dark pattern type with each study focus within the corpus.

Addressed Harm

31 records addressed at least one type of harm

Of the 52 papers in our literature corpus, 21 could not be classified as addressing a specific harm to the user, as outlined in Section 3.1.3. We aligned our analysis with the harms described by the OECD [2022], which include `User Autonomy`, `Financial Loss`, `Privacy Breach`, `Psychological Detriment and Time Loss`, `Weaker or Distorted Competition`, and `Reduced Consumer Trust and Engagement`.

Four harms were researched more extensively than the others

`Privacy Breach` was the most frequently addressed harm in the literature, accounting for 65% of the research papers discussing user harm. This was closely followed by `Psychological Detriment and Time Loss`, which were noted in 61% of the cases. Additionally, `User Autonomy` and `Financial Loss` were addressed in 52% of the papers. In contrast, the issues of `Weaker or Distorted Competition` (n=7) and `Reduced Consumer Trust and Engagement` (n=2) received considerably less attention. A more detailed distribution of these harms over the years is illustrated in Figure 3.17.

A frequency matrix describes the conjunction of dark pattern and harms addressed

The heatmap presented in Figure 3.18 demonstrates a similar trend. Notably, `Privacy Breach` is most frequently associated with the dark pattern `Interface Interference`, which was coded together in 33% of the cases. In contrast, for `Psychological Detriment` and `Time Loss`, the dark pattern `Social Engineering` appeared most often. These were coded together in 29% of the cases.

Platforms

Six papers could not be assigned to a platform

We coded 46 publications in our corpus according to platform types as defined in Section 3.1.3. The platforms were classified as `E-Commerce`, `Entertainment`, `Gaming`, `Generic`, `Navigation`, `Safety Technology`, and `Social Media`.

Our analysis revealed that `E-Commerce` was the most explored platform, with approximately 40% of the papers coded under this category. `Generic` platforms were also

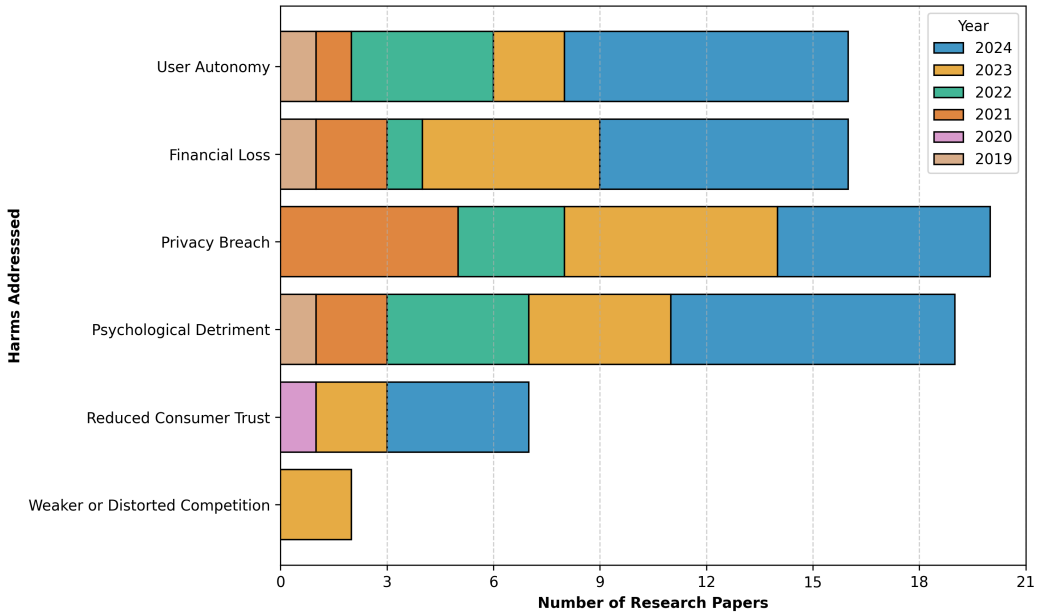

Figure 3.17: This histogram represents the prevalence of harms addressed as coded in 31 papers within the corpus, highlighting the number of papers categorising each type of harm and sorting them by year of publication.

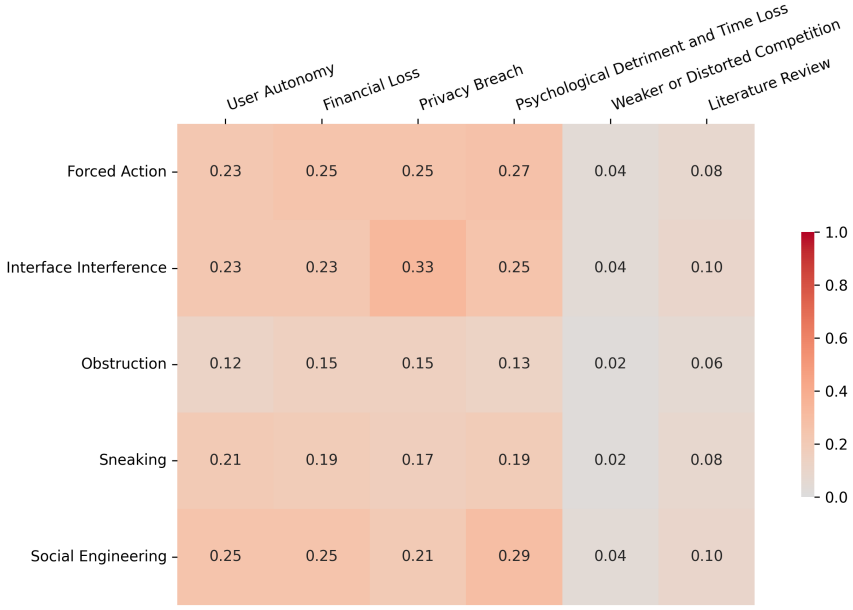

Figure 3.18: This heatmap illustrates the frequency matrix representing the co-occurrence of each dark pattern type with each addressed harm within the corpus.

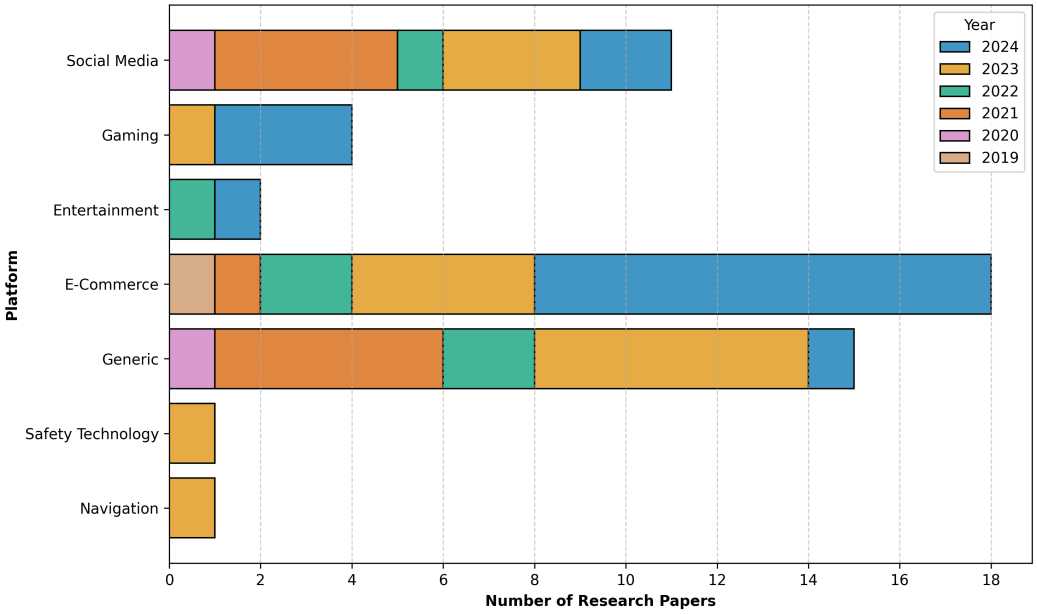

Figure 3.19: This histogram represents the prevalence of platforms coded in 46 papers within the corpus. It highlights the number of papers categorising each platform and sorts them by year of publication.

The volume of research on each platform varied considerably

extensively studied, accounting for 32% of the papers, followed by `Social Media`, which appeared in 24% of the publications. On the other hand, `Safety Technology` and `Navigation` were rarely mentioned - each appearing in only one instance. Figure 3.19 illustrates the frequency of studies on each platforms over the years.

`Social Engineering` was predominantly observed with `E-Commerce`, while `Interface Interference` was mainly observed with `Generic`

The frequency matrix in Figure 3.20 illustrates the occurrence of each platform type in conjunction with dark patterns across our literature corpus. A notable observation is that within `E-Commerce` platforms, the most frequently used dark pattern was `Social Engineering`, with the two items being coded together in 27% of the papers. In contrast, for `Generic` platforms, the most common dark pattern was `Interface Interference`. These two codes appeared together in 25% of the cases.

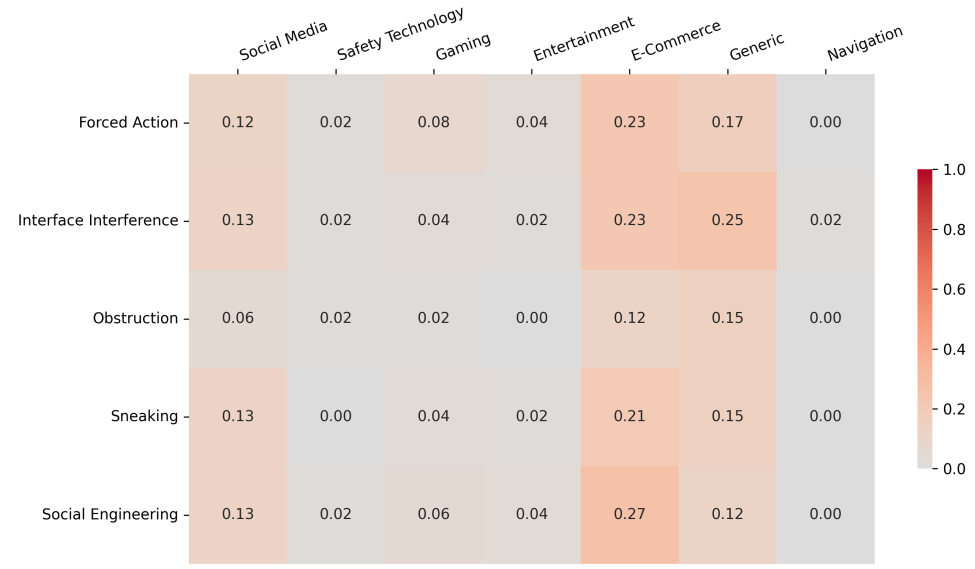

Figure 3.20: This heatmap illustrates the frequency matrix representing the co-occurrence of each dark pattern type with each platform within the corpus.

Country

Less than half of the papers specified a country for the research

In our dataset, 44% (n=23) of the papers explored dark patterns within a culture-specific context. The remaining literature either included an international audience or did not specify a particular country. Figure 3.21 illustrates the distribution of research papers across various countries. Notably, three papers focused on multiple cultures, and one examined participants from several EU countries without emphasising any specific nation. Additionally, 10 culture-specific papers were published in 2024. Table B.3 provides a comprehensive overview of all the countries represented in the reviewed literature, along with the corresponding references.

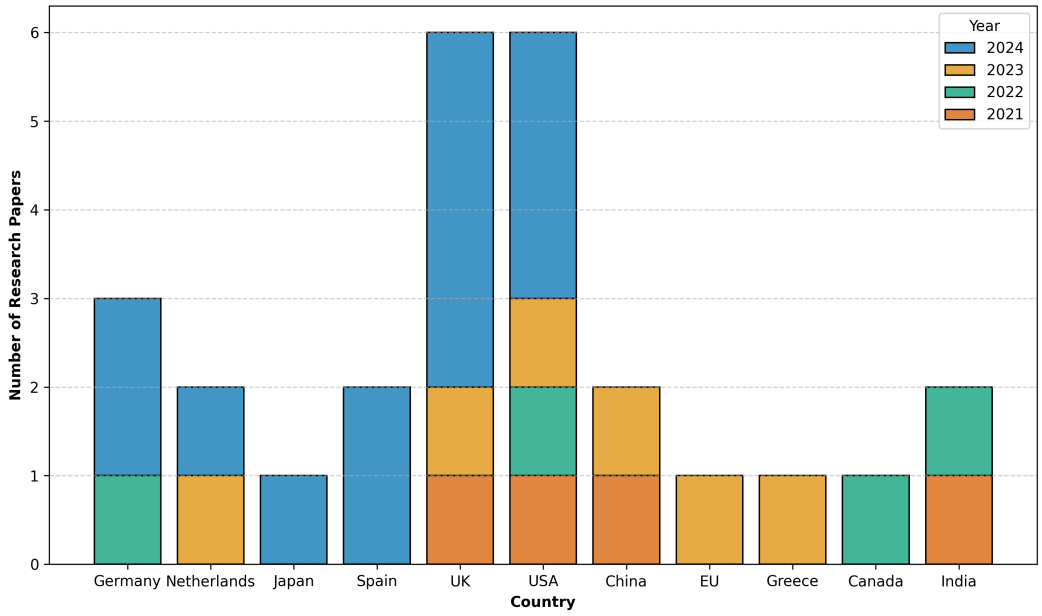

Figure 3.21: This histogram represents the distribution of dark pattern research across countries, with a total of 23 papers attributed to specific countries.

Chapter 4

Evaluation

The following chapter examines the final results concerning the four research questions outlined in Chapter 1. We also compare our results with similar recent contributions and discuss the study's limitations.

4.1 Discussion

We conducted a systematic literature review of 52 research papers focused on dark patterns and published through various conferences and journals from 2019 to August 2024. In the following sections, we will aim to address the research questions outlined in Chapter 1 by drawing on the findings from our meta-analysis. Additionally, we will compare our results with existing literature reviews, such as those by Gray et al. [2023], Nie et al. [2024], and Zielke [2024].

In the following sections, we will provide an overview of dark pattern research in the past (RQ1), explore the impact of dark patterns on users (RQ2), and examine how countermeasure research has evolved (RQ3). Finally, we will conclude by predicting potential future trajectories in dark pattern research (RQ4).

4.1.1 Dark Patterns Over Recent Years

The annual volume of dark pattern contributions reflects the observations made by Lukoff et al. [2021]

Research on dark patterns has expanded rapidly over the past five years, as shown in Figure 4.1, aligning with trends noted by Lukoff et al. [2021]. We observed more conference publications than journal articles, a trend also observed by Gray et al. [2023], though there was a slight dip in 2022. This finding was similar to one by Zielke [2024]. Our corpus screening highlighted a predominant focus on the impact of dark patterns on users, with `IMP` being the most common theme. However, few studies addressed legislation, possibly due to the computer science focus of our data sources, such as ACM Digital Library and IEEE Xplore. A broader search, like one on Google Scholar, might provide a wider cross-disciplinary view. Additionally, with the rise of accessible technologies like VR [Hamad and Jia, 2022], an increasing number of papers have started to explore dark patterns in these spaces, although user interaction with such patterns remains comparatively underexplored.

Distribution of contribution types compared to Zielke [2024]

In our corpus, we identified a higher number of `Empirical` contributions, followed by `Artifact` contributions. While this aligns with the findings of Zielke [2024], we noted a significant difference in the volume of publications containing other contribution types, such as `Methodological` and `Theoretical`. This discrepancy may have been due to our eligibility criteria, which focused on research papers that examined the impact of dark patterns on users and the development of countermeasures. Despite this, our identification and screening phase supports Zielke [2024], as many papers emphasised efforts to create a unified interpretation of dark patterns (`SHA`) and included literature reviews on manipulation in emerging areas like VR [Hadan et al., 2024].

Dark pattern types observed compared to Zielke [2024]

Among the dark patterns studied, we observed that `Interface Interference` received the most attention. Similarly, Zielke [2024] highlighted the extensive study of `Forced Action`, which was also prominent in our findings. Interestingly, Zielke [2024] used the earlier ontology proposed by Gray et al. [2023], where the dark pattern "Nagging" was a high-level category, and "Attention Capture"

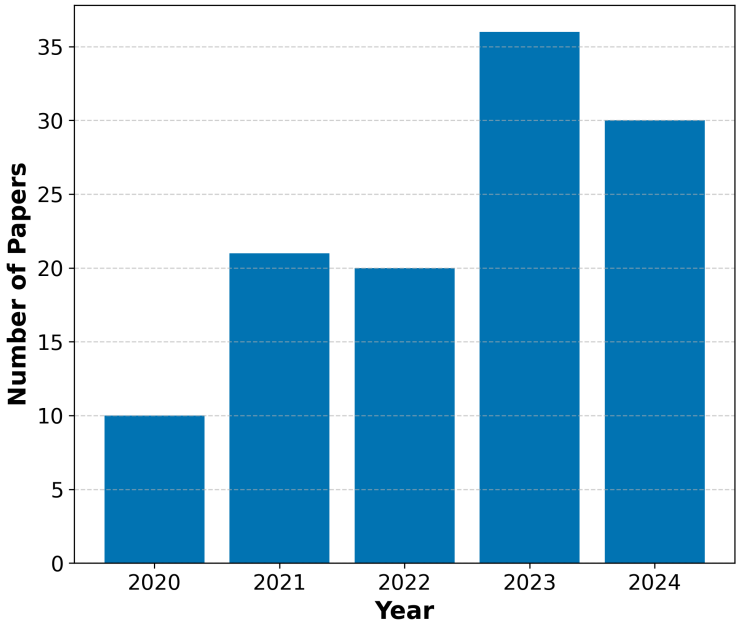

Figure 4.1: This histogram displays the number of dark pattern research papers identified in the literature search over the years. The increase in the number of papers mirrors the trend discussed by Lukoff et al. [2021], though the histogram only represents data up to August 2024.

was not yet identified. In our coding, based on Gray et al. [2024], both have been classified as meso-level dark patterns under `Forced Action`. Additionally, Zielke [2024] pointed out that the research community only started focusing on `Social Engineering` around 2019. Although our literature review does not cover research before 2020, we can confirm that `Social Engineering` has become a well-explored dark pattern type in the past five years.

Research method used in the past five years

The most frequently used research method in the studies was `Questionnaire`, likely due to its ability to reach a larger sample with fewer logistical barriers. A set of structured questions can easily be distributed online, allowing participants to respond from the comfort of their homes. Interestingly, the use of the `Lab Study` and `Interview` methods has also gained momentum since 2021. However, there were no such studies in 2022, likely due to the impact of COVID-

19, corroborating Zielke [2024]'s observation that the pandemic hindered dark pattern research, particularly methods that require in-person interactions. Another noteworthy trend is the recent rise of `Focus Group` studies, which includes workshops and group discussions. This aligns with Zielke [2024]'s finding that "brainstorming" as a research method has gained popularity in recent years.

`Focus Group` as a research method has recently been adopted

4.1.2 Impact on Users

There has been an evolution in `DP Susceptibility` over the past five years

Dark patterns often lead to consequences that vary in magnitude, but the question remains: how detectable are these patterns to the average user? In our corpus, 16 papers were coded under the study focus of `DP Susceptibility`. The research investigating user detection of dark patterns examined all classified dark patterns, with `Interface Interference` being the most frequently studied. Over the past five years, research results on `DP Susceptibility` have evolved. In 2020, Di Geronimo et al. [2020] noted that most users fail to recognise dark patterns unless informed about them. By 2021, M. Bhoot et al. [2021] observed an increase in awareness, although this was still in its early stages. Interestingly, Bongard-Blanchy et al. [2021] claimed in 2021 that while users may be aware of dark patterns, they can still be deceived by them. More recent research, such as that by Sánchez Chamorro et al. [2024a] and Renaud et al. [2024], indicates a higher level of awareness among participants.

Compared to Gray et al. [2023], we found more research papers on `E-Commerce`

Within our literature corpus, we identified a significant focus on `E-Commerce` platforms, with `Generic` platforms being the second most frequently researched. This finding contradicts Gray et al. [2023], who observed more literature contributions concerning "digital services," equivalent to our `Generic` category. The discrepancy arose because Gray et al. [2023] conducted their literature search in September 2022, while many of the papers in our dataset coded with `E-Commerce` were published after 2022. This shift indicates that the research community has recently directed more attention towards online shopping platforms. Additionally, we observed a trend towards specialisation in research fo-

cusing on specific platform types, such as safety technology [Chordia et al., 2023] and navigation [Bongard-Blanchy et al., 2023] , indicating a growing interest in exploring diverse contexts. Furthermore, user studies are no longer confined to desktop interfaces; researchers have expanded their investigations to include contexts such as CUI [Dubiel et al., 2024] and mobile apps [Di Geronimo et al., 2020].

New platforms are being explored in dark pattern research

Similar to the findings of Nie et al. [2024], we observed that the first four harms described by the OECD [2022]—`User Autonomy`, `Financial Loss`, `Privacy Breach`, and `Psychological Detriment and Time Loss`—were explored more frequently. In contrast, harms related to structural user detriment, `Weaker or Distorted Competition` and `Reduced Consumer Trust and Engagement`, received less attention. Additionally, `Privacy Breach` and `Interface Interference` were extensively studied, indicating a strong focus on research involving user consent, a trend also noted by Gray et al. [2023] in the context of consent banners.

Personal user and user autonomy detriment were comparatively more investigated

A recent trend in dark pattern research is the growing focus on specialised study samples. Research has expanded to examine the influence of dark patterns in different cultural contexts. However, such studies have predominantly emerged from countries with established laws against dark patterns, suggesting that these societies are more aware of the issue. No studies were identified in regions such as Africa or Latin America during the course of this review. Additionally, since 2023, researchers have begun investigating the effects of dark patterns on specific age groups, such as children [Fitton et al., 2024; Renaud et al., 2024] and older adults [Sánchez Chamorro et al., 2024a].

Culture-specific and age-specific research is receiving increasing attention

4.1.3 Countermeasures to Dark Patterns

Since 2023, `Countermeasure Proposal` has gained momentum as researchers develop tools to mitigate the influence of dark patterns on users. These detection tools utilise methods like text and colour analysis and are applied across various platforms, including `E-Commerce`, `Entertainment`,

`Countermeasure Proposal` has been on the rise since 2023

and `Social Media`. In our corpus, we identified that a countermeasure was proposed for every dark pattern type. However, not all dark patterns can be detected automatically, as their design can vary significantly, making detection more challenging. This challenge was also noted by Nie et al. [2024], who emphasised the complexity of developing universal detection mechanisms for dark patterns.

Not all dark pattern types are equally addressed in countermeasure research

`Countermeasure Impact` studies remain scarce and do not cover all dark patterns equally, with most countermeasures focusing on cookie consent and detecting GDPR violations. Researchers have only recently begun testing countermeasures on `E-Commerce` platforms to observe how users interact with them. However, most studies have focused on detecting dark patterns within datasets, with fewer exploring how the average user responds to these interventions. There is a pressing need to assess whether existing dark pattern countermeasures are comprehensible and effective for users.

Countermeasures must address users' lack of awareness regarding dark pattern

Furthermore, many proposed countermeasures include an educational component, which underscores the necessity for users to become more aware of dark patterns and their potential consequences. Even the most well-designed countermeasures might not be effective if the user does not have a sufficient understanding of how dark patterns operate. Most current countermeasures are limited to detecting dark patterns and informing users, but this approach alone is insufficient. If users lack the awareness or knowledge to recognise the manipulation tactics, they may still fall prey to these deceptive designs despite the warnings. To improve the effectiveness of countermeasures, future detection tools should focus on identifying dark patterns and incorporating strategies to educate users about the risks. Additionally, countermeasures should be tailored to accommodate varying user awareness levels, ensuring that even less-informed individuals are protected from dark pattern exploitation.

Other countermeasures, such as establishing ethical guidelines for UI designers and introducing legislation prohibiting dark patterns on platforms, were not explored in detail during our literature review. However, during our identi-

fication and screening phase, we observed that both the research and legislative communities have made significant strides in this area to protect consumers. While not the focus of our study, these initiatives are essential methods that contribute to the broader efforts to combat dark patterns. By addressing the issue from a design and regulatory perspective, these measures complement technological countermeasures and play a crucial role in safeguarding user interests.

Ethical and legislative countermeasures were not included in this review

4.1.4 Dark Patterns in Future

The development of dark patterns is likely to continue expanding as more domains begin to take an interest in their study. Emerging fields will likely focus on identifying dark patterns that manipulate users in their specific areas, potentially leading to new taxonomies or extensions of existing ones. Additionally, as research continues, new types of dark patterns may be discovered in unexplored platforms or interfaces.

Dark pattern are an emerging areas of research in other fields

As this field of research evolves, there is also a growing interest in understanding the impact of dark patterns on specific populations. This could lead to extensive studies on the effects of dark patterns on children, who have increasing access to the internet, or older adults, who may lack technological expertise. Furthermore, dark patterns' impacts on vulnerable groups will likely receive more attention, as well as how different cultures from the East to the West interact with dark patterns across various interfaces. These insights would help the research community develop more effective countermeasures tailored to diverse environments.

Dark pattern research aims to expand understanding of various age groups and cultures

Regarding countermeasure development, researchers are expected to focus on creating more user-friendly solutions, enabling users to detect dark patterns more easily on their interfaces. Additionally, further advancements will likely aim to enhance detection mechanisms, allowing countermeasures to cover a broader range of dark patterns, thereby

Countermeasure research should involve more users

providing more comprehensive protection against manipulative design practices.

`Lab Study` and `Focus Group` are likely to be used more frequently as research methods

Another anticipated trend is a shift towards conducting more `Lab Study` and `Focus Group` research. These methods allow researchers to better understand the effects and experiences of users and offer valuable insights into how dark patterns are perceived in controlled settings. Additionally, with approximately 15 years having passed since Brignull et al. [2023] first coined the term 'dark pattern', the field has seen substantial growth across various disciplines. We also anticipate an increase in `Survey` contributions, as these studies enable researchers to capture a comprehensive overview of the state of dark pattern research. This broader approach will expand the range of insights and provide a clearer understanding of emerging trends and their implications across different domains.

4.2 Limitations

Stricter eligibility criteria resulted into a smaller corpus

While completing this bachelor's thesis, we encountered several challenges that were difficult to mitigate. Primarily, given the limited resources available for a bachelor's thesis, this literature review represents only a subset of dark pattern research from the last five years. The eligibility criteria were specifically designed to address our research questions, which may have led to the exclusion of studies offering different perspectives or alternative themes.

Underappreciated dark pattern research in other domains

As a result, compared to Nie et al. [2024] and Gray et al. [2023], our corpus comprised a relatively smaller number of records. Consequently, we may have unintentionally undervalued the development of dark pattern research in other domains, such as gaming and VR, which could have provided a more comprehensive assessment of future trajectories in dark pattern research. This limitation restricted our ability to capture the broader scope of emerging fields and trends.

Data collection method could be broader

Additionally, we conducted our initial literature search using only two databases, which likely limited our access to

important contributions. After defining the corpus of literature, we also observed that the search engines missed some relevant studies despite fitting our screening and eligibility criteria. Consequently, there is a chance that some relevant papers were not identified during our search.

Codebook could have been more precise

Furthermore, our codebook could have been more precise, which would have facilitated a more detailed analysis. This could have been achieved by analysing dark pattern types at the meso-level rather than just the high-level dark pattern types. However, this approach would have risked creating an excessive number of categories, potentially hindering constructive analysis in every context. Nevertheless, it may have been possible to identify meso-level patterns within the codebook for more frequently occurring dark pattern types. The same consideration applies to other categories in our codebook.

Possibility of human error

Lastly, the coding of the papers was conducted by a single person. Although the coding process was repeated multiple times and a small incubation period was implemented to allow for a fresh perspective, the possibility that a paper was misinterpreted or there was human error cannot be entirely ruled out. Despite efforts to minimise these risks, the absence of a second reviewer introduced some potential for subjective bias in the analysis.

Chapter 5

Summary and Future Work

The following chapter presents a summary and overview of this thesis's contributions. Based on our findings, we conclude the thesis by suggesting future research directions.

5.1 Summary and Contributions

Overall summary

In this thesis, we conducted a systematic literature review following the PRISMA guidelines by Page et al. [2021] to evaluate research on dark patterns since 2020. Our research questions focused on how the academic community has studied the impact of dark patterns on users, as well as the development of countermeasures to address these patterns. In conclusion, we hope to have provided a meaningful overview of dark pattern research related to user impact and the ongoing development of countermeasures.

Summary of dark pattern research in recent years

Our results indicated that `Interface Interference` was the most extensively explored dark pattern in our corpus, closely followed by `Forced Action`. In contrast, `Obstruction` received the least attention. Additionally, there was a notable prevalence of `Empirical` and `Artifact` contributions. While `Questionnaire` was the predominant

research method employed, other approaches, such as the `Lab Study` and `Focus Group`, have begun to gain momentum.

Summary of dark pattern's impact on users

We observed a notable shift in the literature regarding user awareness of dark patterns. Studies indicate that while users are increasingly aware of dark patterns, many still succumb to their influence. The existing research primarily focuses on user reactions on `E-Commerce` and `Generic` platforms, with specific platforms also emerging as topics of research interest. Although four of the harms outlined by the OECD [2022] have been frequently examined, the cumulative impact of dark patterns on consumers as a whole remains underexplored.

Summary of countermeasure research

Over the past two years, researchers have begun to examine how users respond to dark patterns when countermeasures are implemented and explore various strategies for mitigating their effects. The development of dark pattern detection tools employs various techniques; however, these solutions are not yet easily accessible to the average user. As a result, user education remains a vital component in reducing the harms associated with dark patterns.

5.2 Future Work

Expanding the corpus criteria for a broader perspective

Future work following this thesis could include broadening the scope of eligibility criteria to gain a more comprehensive perspective on dark pattern research. For instance, researchers could expand their literature search queries across various databases, utilise search engines not included in this study, and incorporate dark pattern synonyms identified over the years. This approach could lead to a larger corpus of literature records and offer a deeper understanding of the field.

Expanding the codebook for a detailed overview

Moreover, future research could expand dark pattern coding and examine how meso-level or low-level dark pattern types are represented in the literature. How many of these patterns are detectable, what their impacts on users are, and how susceptible different demographic groups are

to these patterns are essential questions that remain unexplored and could be addressed through empirical studies involving human participants.

Dark pattern research in other domains

Additionally, there is potential for researchers to investigate how dark patterns manifest in new domains where research is limited. Understanding how the number and nature of dark patterns evolve in these areas, especially as they become more available to the average user, would be a valuable line of inquiry.

Annual reviews to map the expanding dark pattern research

Finally, an innovative direction for future research could involve producing periodic literature reviews on dark patterns - perhaps annually. This would allow for an evaluation of how dark patterns develop across disciplines such as law, ethics, psychology, and human-computer interaction. Although this endeavour would be labour-intensive, it could serve as a significant resource for researchers seeking to track the evolution of dark patterns over time.

Appendix A

Unscreened Dataset

The Table A.1 below provides an overview of the identified dataset, with the detailed collection process described in Section 3.2. It includes the conference, journal or magazine where each work was published, denoted by "(C)" for conferences, "(J)" for journals and "(M)" for magazines, and the category assigned to each entry, as explained in Section 3.2.

Furthermore, we specify the source of each paper: papers retrieved from the ACM Digital Library are tagged as ACM, those from IEEE Xplore are labeled I3E, and records sourced from references are marked as REF.

Lastly, the table indicates whether the paper was deemed eligible for inclusion in our literature review, with a "✓" representing selection and a "✗" indicating exclusion.

Reference	Conference or Journal	Type	Derived from	Eligibility
[Albuquerque et al., 2024]	PACMHCI (J)	IMP	ACM	✓
[Babaei and Vassileva, 2024]	FAccT (C)	COU	ACM	✓
[Berens et al., 2022]	ARES (C)	IMP	ACM	✓
[Bermejo Fernandez et al., 2021]	PACMHCI (J)	IMP	ACM	✓
[Bongard-Blanchy et al., 2021]	DIS (C)	IMP	ACM	✓
[Bongard-Blanchy et al., 2023]	EuroUSEC (C)	IMP	ACM	✓
[Chang et al., 2024]	CHI EA (C)	SHA	ACM	✓
[Chaudhary et al., 2022]	DIS (C)	IMP	ACM	✓
[Chen et al., 2023]	UIST (C)	COU	ACM	✓
[Chordia et al., 2023]	CHI (C)	IMP	ACM	✓
[Di Geronimo et al., 2020]	CHI (C)	IMP	ACM	✓
[Dubiel et al., 2024]	IUI (C)	IMP	ACM	✓
[Fitton et al., 2024]	IHC (C)	IMP	ACM	✓
[Gray et al., 2021]	PACMHCI (J)	IMP	ACM	✓
[Gray et al., 2024]	CHI (C)	SHA	ACM	✓
[Gundelach and Herrmann, 2023]	ARES (C)	COU	ACM	✓
[Habib et al., 2022]	CHI (C)	IMP	ACM	✓
[Inal et al., 2024]	ETRA (C)	IMP	ACM	✓
[Jafari and Vassileva, 2024]	UMAP (C)	COU	ACM	✓
[Kaneko et al., 2024]	DIS (C)	COU	ACM	✓
[Keleher et al., 2022]	NordiCHI (C)	IMP	ACM	✓
[King et al., 2023]	PACMHCI (J)	IMP	ACM	✓
[Kirkman et al., 2023]	EuroS&P (C)	COU	I3E	✓
[Kollnig et al., 2021]	CHI EA (C)	COU	ACM	✓
[Kontogeorgou et al., 2023]	ECCE (C)	IMP	ACM	✓
[M. Bhoot et al., 2021]	IndiaHCI (C)	IMP	ACM	✓
[Mansur, 2023]	ICSE (C)	COU	ACM	✓
[Mansur et al., 2023]	ICSE (C)	COU	ACM	✓
[Mathur et al., 2019]	PACMHCI (J)	COU	REF	✓
[Mathur et al., 2021]	CHI (C)	SHA	ACM	✓
[Mejtoft et al., 2023]	ECCE (C)	IMP	ACM	✓

Continued on next page

Reference	Conference or Journal	Type	Derived from	Eligibility
[Mildner and Savino, 2021]	CHI EA (C)	IMP	ACM	✓
[Mildner et al., 2023]	DIS (C)	IMP	ACM	✓
[Nazarov and Yerkebulan, 2022]	Mathematics (J)	COU	REF	✓
[Nie et al., 2024]	PACMSE (J)	SHA	ACM	✓
[Renaud et al., 2024]	TOCHI (J)	IMP	ACM	✓
[Sánchez Chamorro et al., 2024a]	DIS (C)	IMP	ACM	✓
[Sanchez Chamorro et al., 2024b]	DIS (C)	IMP	ACM	✓
[Salina and Sangaraju, 2021]	ICSADL (C)	COU	REF	✓
[Sazid et al., 2023]	APSEC (C)	COU	I3E	✓
[Schaffner et al., 2022]	PACMHCI (J)	IMP	ACM	✓
[Schäfer et al., 2023]	MuC (C)	COU	ACM	✓
[Schäfer et al., 2024]	CHI (C)	COU	ACM	✓
[Seaborn et al., 2024]	CHI EA (C)	IMP	ACM	✓
[Sheil et al., 2024]	CHI (C)	IMP	ACM	✓
[Shi et al., 2024]	WWW (C)	COU	ACM	✓
[Stavrakakis et al., 2021]	AIT (J)	COU	REF	✓
[Swart et al., 2020]	CHI (C)	COU	ACM	✓
[Tiemessen et al., 2023]	CHI EA (C)	IMP	ACM	✓
[Vigh et al., 2024]	DIS (C)	COU	ACM	✓
[Westin and Chiasson, 2021]	CHI (C)	IMP	ACM	✓
[Wu et al., 2023]	TOCHI (J)	IMP	ACM	✓
[Aagaard et al., 2022]	CHI (C)	ETH	ACM	✗
[Ahuja and Kumar, 2024]	EduCHI (C)	ETH	ACM	✗
[Alberts et al., 2024]	PACMHCI (J)	ETH	ACM	✗
[Aliman and Kester, 2020]	AIVR (C)	TRD	I3E	✗
[Anne de Haas and Lee, 2022]	ISMARW (C)	TRD	I3E	✗
[Avanesi et al., 2023]	CUI (C)	OTH	ACM	✗
[Baroni et al., 2021]	IHC (C)	SHA	ACM	✗
[Birk et al., 2023]	CHI EA (C)	OTH	ACM	✗
[Birk et al., 2024]	GAMES (J)	TRD	ACM	✗
[Caragay et al., 2024]	CHI (C)	ETH	ACM	✗

Continued on next page

Reference	Conference or Journal	Type	Derived from	Eligibility
[Dickinson et al., 2022]	CHI EA (C)	TRD	ACM	✗
[Dula et al., 2023]	SIEDS (C)	TRD	I3E	✗
[Eghtebas et al., 2023]	DIS (C)	TRD	ACM	✗
[Feng et al., 2023]	ICBDA (C)	SHA	I3E	✗
[Freeman et al., 2022]	PACMHCI (J)	ETH	ACM	✗
[Frommel et al., 2023]	CHI-PLAY (C)	OTH	ACM	✗
[Gray et al., 2020]	DIS (C)	ETH	ACM	✗
[Gray et al., 2021]	ICER (C)	ETH	ACM	✗
[Gray et al., 2021]	CHI (C)	LAW	ACM	✗
[Gray et al., 2023]	CHI EA (C)	OTH	ACM	✗
[Gray et al., 2023]	CHI EA (C)	OTH	ACM	✗
[Gray et al., 2023]	CHI EA(C)	SHA	ACM	✗
[Gray et al., 2023]	DIS (C)	SHA	ACM	✗
[Gray et al., 2024]	CHI EA (C)	OTH	ACM	✗
[Gunawan et al., 2021]	PACMHCI (J)	SHA	ACM	✗
[Gunawan et al., 2022]	CSLAW (C)	LAW	ACM	✗
[Hadan et al., 2024]	CSUR (J)	TRD	ACM	✗
[Hidaka et al., 2023]	CHI (C)	SHA	ACM	✗
[Hodent et al., 2024]	GAMES (J)	ETH	ACM	✗
[Hogan et al., 2022]	ToCHI (J)	TRD	ACM	✗
[Kender and Frauenberger, 2022]	DIS (C)	TRD	ACM	✗
[Kollnig et al., 2023]	FAccT (C)	ETH	ACM	✗
[Kowalczyk et al., 2023]	CHI (C)	TRD	ACM	✗
[Krauß et al., 2024]	TOCHI (J)	TRD	ACM	✗
[Krisam et al., 2021]	EuroUSEC (C)	SHA	ACM	✗
[Kyi et al., 2023]	CHI (C)	LAW	ACM	✗
[Lacey and Caudwell, 2020]	HRI (C)	TRD	ACM	✗
[Lindblom et al., 2024]	ARSO (C)	TRD	I3E	✗
[Long et al., 2023]	CCS (C)	SHA	ACM	✗
[Lu et al., 2024]	PACMHCI (J)	ETH	ACM	✗
[Lukoff et al., 2021]	CHI EA (C)	OTH	ACM	✗
[Mathur, 2021]	CHI EA (C)	OTH	ACM	✗
[Mildner et al., 2022]	CUI (C)	ETH	ACM	✗
[Mildner et al., 2023]	CHI (C)	SHA	ACM	✗
[Mildner et al., 2024]	CHI (C)	TRD	ACM	✗
[Miranda et al., 2022]	IHC (C)	ETH	ACM	✗

Continued on next page

Reference	Conference or Journal	Type	Derived from	Eligibility
[Monge Roffarello and De Russis, 2022]	CHI (C)	SHA	ACM	✗
[Monge Roffarello et al., 2023]	CHI (C)	SHA	ACM	✗
[Morel et al., 2022]	CCS (C)	LAW	ACM	✗
[Narayanan et al., 2020]	CACM (M)	SHA	ACM	✗
[Nouwens et al., 2020]	CHI (C)	LAW	ACM	✗
[Owens et al., 2022]	EuroUSEC (C)	TRD	ACM	✗
[Rogers et al., 2021]	CHI EA (C)	OTH	ACM	✗
[Rogers et al., 2020]	CHI EA (C)	OTH	ACM	✗
[Sánchez Chamorro, 2023]	CHI EA (C)	OTH	ACM	✗
[Sánchez Chamorro et al., 2023]	DIS (C)	ETH	ACM	✗
[Soe et al., 2020]	NordiCHI (C)	LAW	ACM	✗
[Tahaei and Vaniea, 2021]	CHI EA (C)	ETH	ACM	✗
[Tiangpanich and Nimkoompai, 2022]	ICBIR (C)	ETH	I3E	✗
[Van Hofslot et al., 2022]	NLLP (C)	OTH	ACM	✗
[Wagner et al., 2020]	FAT* (C)	LAW	ACM	✗
[Warberg et al., 2023]	CCS (C)	LAW	ACM	✗
[Westin and Chiasson, 2020]	NSPW (C)	SHA	ACM	✗
[Yada et al., 2022]	Big Data (C)	SHA	I3E	✗
[Yada et al., 2023]	BigData (C)	SHA	I3E	✗
[Zeng et al., 2021]	IMC (C)	SHA	ACM	✗
[Zhang-Kennedy et al., 2024]	PACMHCI (J)	ETH	ACM	✗

Table A.1: 118 literature contributions were identified after the literature search

Appendix B

Screened Dataset

This appendix provides a detailed summary of the 52 papers analyzed throughout this thesis. For clarity, the appendix is divided into three distinct tables. Table B.1 presents the contribution type, research method, and dark patterns addressed in each paper. Table B.2 outlines the study focus, harms discussed, and the platform emphasized in each paper. Finally, Table B.3 lists all papers that focused on research conducted in a specific country. Papers not listed in Table B.3 either did not address a particular country or targeted a global audience, for example, through international surveys.

Reference	Contribution Type	Research Method	Dark Patterns Addressed
[Albuquerque et al., 2024]	Empirical, Survey	Literature Review	Forced Action, Interface Interference, Sneaking, Social Engineering
[Babaei and Vassileva, 2024]	Empirical	Questionnaire	Not Specific
[Berens et al., 2022]	Empirical	Questionnaire	Interface Interference
[Bermejo Fernandez et al., 2021]	Empirical	Questionnaire	Forced Action, Interface Interference
[Bongard-Blanchy et al., 2021]	Empirical	Questionnaire	Forced Action, Interface Interference, Sneaking, Social Engineering
[Bongard-Blanchy et al., 2023]	Empirical	Questionnaire	Interface Interference
[Chang et al., 2024]	Survey	Literature Review	Not Specific
[Chaudhary et al., 2022]	Empirical	Field Study	Forced Action, Interface Interference, Social Engineering
[Chen et al., 2023]	Artifact, Dataset	Literature Review, Question-naire	Forced Action, Interface Interference, Obstruction, Sneaking, Social Engineering
[Chordia et al., 2023]	Empirical, Theoretical	Interview	Forced Action, Interface Interference, Obstruction, Social Engineering

Continued on next page

Reference	Contribution Type	Research Method	Dark Patterns Addressed
[Di Geronimo et al., 2020]	Dataset, Empirical	Field Study, Questionnaire	Forced Action, Interface Interference, Obstruction, Sneaking
[Dubiel et al., 2024]	Empirical	Questionnaire	Interface Interference
[Fitton et al., 2024]	Empirical	Lab Study, Questionnaire	Forced Action, Social Engineering
[Gray et al., 2021]	Empirical	Interview, Questionnaire	Forced Action, Interface Interference, Obstruction, Sneaking, Social Engineering
[Gray et al., 2024]	Survey, Theoretical	Literature Review	Not Specific
[Gundelach and Herrmann, 2023]	Artifact, Dataset	Not Specific	Interface Interference, Obstruction
[Habib et al., 2022]	Empirical	Field Study, Questionnaire	Forced Action, Interface Interference, Social Engineering
[Inal et al., 2024]	Empirical	Lab Study	Interface Interference
[Jafari and Vassileva, 2024]	Empirical	Questionnaire	Not Specific
[Kaneko et al., 2024]	Empirical, Methodological	Field Study, Interview	Forced Action, Interface Interference, Sneaking, Social Engineering
[Keleher et al., 2022]	Empirical	Questionnaire	Forced Action, Interface Interference, Obstruction, Sneaking, Social Engineering

Continued on next page

Reference	Contribution Type	Research Method	Dark Patterns Addressed
[King et al., 2023]	Empirical	Questionnaire	Forced Action, Interface Interference, Obstruction
[Kirkman et al., 2023]	Artifact	Field Study	Forced Action, Interface Interference, Obstruction, Sneaking
[Kollnig et al., 2021]	Artifact, Theoretical	Field Study	Not Specific
[Kontogeorgou et al., 2023]	Empirical	Lab Study	Interface Interference
[M. Bhoot et al., 2021]	Empirical, Theoretical	Lab Study, Questionnaire	Forced Action, Interface Interference, Obstruction, Sneaking, Social Engineering
[Mansur, 2023]	Artifact, Dataset	Not Specific	Not Specific
[Mansur et al., 2023]	Artifact, Dataset	Field Study	Forced Action, Interface Interference, Sneaking, Social Engineering
[Mathur et al., 2019]	Artifact, Dataset, Theoretical	Field Study	Forced Action, Interface Interference, Obstruction, Sneaking, Social Engineering
[Mathur et al., 2021]	Methodological, Survey	Literature Review	Not Specific
[Mejtoft et al., 2023]	Empirical	Questionnaire, Focus Group, Lab Study	Interface Interference
[Mildner and Savino, 2021]	Empirical	Field Study, Questionnaire	Interface Interference, Obstruction

Continued on next page

Reference	Contribution Type	Research Method	Dark Patterns Addressed
[Mildner et al., 2023]	Empirical	Focus Group, Questionnaire	Forced Action, Interface Interference, Obstruction, Sneaking, Social Engineering
[Nazarov and Yerkebulan, 2022]	Artifact	Field Study	Forced Action, Interface Interference, Obstruction, Sneaking, Social Engineering
[Nie et al., 2024]	Survey, Theoretical	Literature Review	Not Specific
[Renaud et al., 2024]	Empirical	Focus Group	Forced Action, Sneaking, Social Engineering
[Sánchez Chamorro et al., 2024a]	Empirical	Focus Group	Not Specific
[Sanchez Chamorro et al., 2024b]	Empirical	Interview	Forced Action, Interface Interference, Sneaking, Social Engineering
[Salina and Sangaraju, 2021]	Artifact	Field Study	Not Specific
[Sazid et al., 2023]	Artifact	Not Specific	Forced Action, Obstruction, Sneaking, Social Engineering
[Schaffner et al., 2022]	Empirical	Field Study, Questionnaire	Forced Action, Obstruction, Sneaking, Social Engineering
[Schäfer et al., 2023]	Artifact	Questionnaire	Interface Interference, Social Engineering

Continued on next page

Reference	Contribution Type	Research Method	Dark Patterns Addressed
[Schäfer et al., 2024]	Empirical	Lab Study	Forced Action, Interface Interference, Sneaking, Social Engineering
[Seaborn et al., 2024]	Empirical	Lab Study, Interview	Forced Action, Interface Interference, Obstruction, Sneaking, Social Engineering
[Sheil et al., 2024]	Empirical	Field Study	Obstruction
[Shi et al., 2024]	Methodological	Not Specific	Forced Action, Obstruction
[Stavrakakis et al., 2021]	Artifact, Theoretical	Literature Review	Forced Action, Interface Interference, Obstruction, Sneaking, Social Engineering
[Swart et al., 2020]	Artifact	Field Study, Question-naire	Sneaking
[Tiemessen et al., 2023]	Empirical	Questionnaire	Social Engineering
[Vigh et al., 2024]	Artifact, Empirical	Field Study, Interviews, Question-naire	Forced Action, Interface Interference, Obstruction, Sneaking, Social Engineering
[Westin and Chiasson, 2021]	Empirical, Theoretical	Interview	Social Engineering
[Wu et al., 2023]	Empirical	Field Study, Interview	Forced Action, Interface Interference, Sneaking, Social Engineering

Table B.1: Contribution Type, Research Method and Dark Patterns Addressed in the Reviewed Literature

Reference	Study Focus	Addressed Harms	Platform
[Albuquerque et al., 2024]	Countermeasure Proposal, DP Impact	Privacy Breach, Psychological Detriment and Time Loss, User Autonomy	Social Media
[Babaei and Vassileva, 2024]	Countermeasure Impact	Not Specific	E-Commerce
[Berens et al., 2022]	DP Impact	Privacy Breach, Psychological Detriment and Time Loss, User Autonomy	Generic
[Bermejo Fernandez et al., 2021]	DP Susceptibility	Privacy Breach	Generic
[Bongard-Blanchy et al., 2021]	Countermeasure Proposal, DP Impact, DP Susceptibility	Financial Loss, Privacy Breach, Psychological Detriment and Time Loss	E-Commerce, Social Media
[Bongard-Blanchy et al., 2023]	DP Impact	Privacy Breach, Lesser Consumer Trust and Engagement	Navigation
[Chang et al., 2024]	DP Interpretation	Not Specific	Not Specific
[Chaudhary et al., 2022]	DP Discovery, DP Impact, Taxonomy Construction	Psychological Distress and Time Loss, User Autonomy	Entertainment
[Chen et al., 2023]	Countermeasures Proposal	Not Specific	Generic
[Chordia et al., 2023]	DP Impact, DP Susceptibility, Taxonomy Construction	Financial Loss, Privacy Breach, Psychological Detriment and Time Loss, Weaker or Distorted Competition	Safety Technology

Continued on next page

Reference	Study Focus	Addressed Harms	Platform
[Di Geronimo et al., 2020]	DP Susceptibility	Not Specific	Generic
[Dubiel et al., 2024]	DP Discovery, DP Impact, DP Susceptibility	Not Specific	Generic
[Fitton et al., 2024]	DP Impact	Psychological Detriment and Time Loss	Gaming
[Gray et al., 2021]	DP Impact, DP Susceptibility	Financial Loss, Privacy Breach, Lesser Consumer Trust and Engagement, User Autonomy	Generic
[Gray et al., 2024]	DP Interpretation, Taxonomy Construction	Not Specific	Not Specific
[Gundelach and Herrmann, 2023]	Countermeasure Proposal	Privacy Breach	Generic
[Habib et al., 2022]	DP Impact	Privacy Breach	E-Commerce
[Inal et al., 2024]	DP Impact	Privacy Breach, User Autonomy	E-Commerce
[Jafari and Vassileva, 2024]	Countermeasure Impact, Countermeasure Proposal	Not Specific	E-Commerce
[Kaneko et al., 2024]	Countermeasure Interpretation, DP Impact	Financial Loss, Psychological Detriment and Time Loss, User Autonomy	E-Commerce
[Keleher et al., 2022]	DP Susceptibility	Not Specific	Generic
[King et al., 2023]	DP Discovery, DP Impact, DP Susceptibility	Financial Loss	Gaming
[Kirkman et al., 2023]	DP Discovery, Countermeasure Proposal	Privacy Breach	Generic

Continued on next page

Reference	Study Focus	Addressed Harms	Platform
[Kollnig et al., 2021]	Countermeasure Proposal	Not Specific	Social Media
[Kontogeorgou et al., 2023]	DP Discovery, DP Impact	Psychological Detriment and Time Loss	Social Media
[M. Bhoot et al., 2021]	DP Susceptibility, DP Impact, Taxonomy Construction	Not Specific	Generic
[Mansur, 2023]	Countermeasure Proposal	Not Specific	Generic
[Mansur et al., 2023]	Countermeasure Impact, Countermeasure Proposal	Not Specific	Generic
[Mathur et al., 2019]	Countermeasure Proposal, Taxonomy Construction	Financial Loss, Psychological Distress and Time Loss, User Autonomy	E-Commerce
[Mathur et al., 2021]	DP Interpretation	Not Specific	Not Specific
[Mejtoft et al., 2023]	DP Impact	Privacy Breach, Lesser Consumer Trust and Engagement	Generic
[Mildner and Savino, 2021]	DP Impact, DP Susceptibility	Privacy Breach, Psychological Distress and Time Loss	Social Media
[Mildner et al., 2023]	DP Interpretation, DP Susceptibility	Not Specific	Social Media
[Nazarov and Yerkebulan, 2022]	Countermeasure Proposal	Financial Loss, Privacy Breach, Psychological Distress and Time Loss, User Autonomy	E-Commerce

Continued on next page

Reference	Study Focus	Addressed Harms	Platform
[Nie et al., 2024]	DP Discovery, DP Interpretation, Countermeasure Interpretation, Taxonomy Construction	Not Specific	Not Specific
[Renaud et al., 2024]	DP Impact, DP Susceptibility	Financial Loss, Privacy Breach, User Autonomy	E-Commerce, Entertainment, Gaming
[Sánchez Chamorro et al., 2024a]	DP Susceptibility	Not Specific	Not Specific
[Sanchez Chamorro et al., 2024b]	DP Impact	Financial Loss, Privacy Breach, Psychological Detriment and Time Loss, User Autonomy	E-Commerce, Gaming, Social Media
[Salina and Sangaraju, 2021]	Countermeasure Proposal	Not Specific	Generic
[Sazid et al., 2023]	Countermeasure Proposal	Not Specific	E-Commerce
[Schaffner et al., 2022]	DP Impact	Psychological Detriment and Time Loss, Lesser Consumer Trust and Engagement, User Autonomy	Social Media
[Schäfer et al., 2023]	Countermeasure Impact, Countermeasure Proposal	Financial Loss	E-Commerce
[Schäfer et al., 2024]	Countermeasure Impact	Financial Loss, Psychological Detriment and Time Loss, User Autonomy	E-Commerce

Continued on next page

Reference	Study Focus	Addressed Harms	Platform
[Seaborn et al., 2024]	DP Impact, DP Susceptibility	Financial Loss, Psychological Detriment and Time Loss, Privacy Breach, Lesser Consumer Trust and Engagement, User Autonomy	E-Commerce
[Sheil et al., 2024]	DP Impact	Financial Loss, Psychological Detriment and Time Loss, User Autonomy	E-Commerce
[Shi et al., 2024]	Countermeasure Interpretation	Financial Loss, Privacy Breach, Psychological Detriment and Time Loss	Not Specific
[Stavrakakis et al., 2021]	Countermeasure Interpretation, Countermeasure Proposal	Not Specific	Generic
[Swart et al., 2020]	DP Susceptibility, Countermeasure Impact, Countermeasure Proposal	Not Specific	Social Media
[Tiemessen et al., 2023]	DP Impact	Financial Loss, Lesser Consumer Trust and Engagement, Psychological Distress and Time Loss, User Autonomy	E-Commerce

Continued on next page

Reference	Study Focus	Addressed Harms	Platform
[Vigh et al., 2024]	Countermeasure Proposal, Countermeasure Impact, DP Impact	Not Specific	E-Commerce
[Westin and Chiasson, 2021]	DP Impact	Privacy Breach, Psychological Detriment and Time Loss	Social Media
[Wu et al., 2023]	DP Discovery, DP Impact, DP Susceptibility	Financial Loss, Psychological Detriment and Time Loss, Privacy Breach, Lesser Consumer Trust and Engagement, User Autonomy, Weaker or Distorted Competition	E-Commerce, Social Media

Table B.2: Study Focus, Addressed Harms and Platforms of the Reviewed Literature

Country	Quantity	References
Canada	1	Keleher et al. [2022]
China	2	Gray et al. [2021], Wu et al. [2023]
European Union (EU)	1	Tiemessen et al. [2023]
Germany	3	Berens et al. [2022], Sheil et al. [2024], Schäfer et al. [2024]
Greece	1	Kontogeorgou et al. [2023]
India	2	Chaudhary et al. [2022], M. Bhoot et al. [2021]
Netherlands	2	Kontogeorgou et al. [2023], Sheil et al. [2024]
Japan	1	Seaborn et al. [2024]
Spain	2	Sánchez Chamorro et al. [2024a], Sanchez Chamorro et al. [2024b]
United Kingdom (UK)	6	Bongard-Blanchy et al. [2021], Bongard-Blanchy et al. [2023], Fitton et al. [2024], Renaud et al. [2024], Sheil et al. [2024], Vigh et al. [2024]
United States (US)	6	Chordia et al. [2023], Dubiel et al. [2024], Gray et al. [2021], Kaneko et al. [2024], Schaffner et al. [2022], Sheil et al. [2024]

Table B.3: Country of the Reviewed Literature

Appendix C

Codebook

This appendix offers an extensive description of the codes employed during the eligibility assessment and analysis of the collected corpus. Table C.1 outlines the codes used for the eligibility assessment of the identified set of data, while the subsequent tables detail the codes applied during the analysis of the literature.

Theme	Quantity	Definition
SHA	20	Studies that concentrated on developing a shared taxonomy and offered a more theoretical perspective on dark patterns
IMP	29	Studies that focused on the impact of dark patterns on users, emphasizing how these patterns could affect or harm them
ETH	16	Studies that explored the ethical dimension of dark patterns, offering ethical guidelines for designers or suggesting raising designers' ethical awareness
LAW	8	Studies that examined the legislative aspect of dark patterns, including reports published since the implementation of new laws like GDPR.
COU	19	Studies that focused on researching technical countermeasures
TRD	15	Studies that spanned various domains, including robotics and XR, providing a new context for dark pattern research
OTH	11	Panel papers, SIG papers, workshop papers, and dissertations identified during the literature search

Table C.1: Various Themes of literature identified during the literature search.

Research Contribution	Quantity	Definition
Empirical	34	New findings derived from a systematic data collection method
Artifact	14	Research dedicated towards novel inventions, techniques, tools or designs
Methodological	3	Research focused on developing new methods to enhance research
Theoretical	8	Enhance our understanding of what we do, why we do it, and our expectations
Dataset	6	Corpus of raw data points accompanied by an analysis of their characteristics
Survey	5	Attempts to synthesize research to reveal trends, themes, and gaps
Opinion	0	Persuade readers to reconsider their views by presenting the author's opinion

Table C.2: Seven research contributions in HCI by Wobbrock and Kientz [2016].

Dark Pattern	Quantity	Definition
Forced Action	29	Strategy designed to compel users to take additional actions while preventing them from completing the actions they originally intended
Interface Interference	33	Strategy that manipulates the interface to deceive users into taking actions that are against their best interests
Obstruction	20	Strategy that disrupts a user's task flow, making the task more difficult and thereby hindering the user from completing a desired action
Sneaking	23	Strategy that conceals information which, if disclosed, would likely lead users to avoid taking an action they might otherwise object to
Social Engineering	27	Strategy that leverages the user's cognitive and social behaviors to prompt decisions that are ultimately against their best interests

Table C.3: High-Level dark patterns identified by Gray et al. [2024].

Research Method	Quantity	Definition
Field Study	16	Observation of participants, or tools, in uncontrolled settings
Focus Group	4	Lively discussions, usually in groups, on a particular topic
Lab Study	7	Monitoring of participants in a researcher-controlled setting
Literature Review	7	Evaluation and synthesis of existing research on a specific topic
Interview	8	Less structured questions, allowing in-depth, two-way discussions with participants
Questionnaire	23	Using structured questions directed at a sample of individuals to gain insights

Table C.4: Empirical Research Method identified by Mathur et al. [2021].

Study Focus	Quantity	Definition
Countermeasure Impact	7	Research focused on the impact of countermeasures on users, including their reactions and effects
Countermeasure Interpretation	4	Research concentrated on evaluating countermeasures, their effectiveness, and their impact on various dark patterns
Countermeasure Proposal	17	Research proposes new countermeasures against dark patterns (technical or non-technical)
DP Discovery	7	Research that introduce new and previously unidentified dark patterns
DP Interpretation	5	Research that delves into understanding and gathering dark patterns
DP Impact	26	Research that investigates the impact of dark patterns on users, focusing on how they affect user behavior and decision-making
DP Susceptibility	16	Research that explore how detectable dark patterns are to users and whether they can perceive their presence
Taxonomy Construction	6	Research that proposes a new taxonomy for categorizing dark patterns

Table C.5: Study Focus identified in the literature corpus.

Harms to Users	Quantity	Definition
User Autonomy	16	Pressuring users into making choices they would not otherwise make, restricting available options, and obscuring the decision-making process
Financial Loss	16	Coerce consumers into making unnecessary purchases or overspending
Privacy Breach	20	Encourage users to unintentionally share excessive personal information
Psychological Detriment and Time Loss	19	Impose emotional and cognitive stress on users, manipulating their vulnerabilities and/or resulting in wasted time
Weaker or Distorted Competition	2	Skew market competition by obstructing or deterring consumers from exploring and comparing different offers
Reduced Consumer Trust and Engagement	7	Undermine consumer trust and engagement by misleading users into oversharing personal information or overspending

Table C.6: Harms on the users as identified by OECD [2022].

Platform	Quantity	Definition
Social Media	11	Offer users to connect, interact and share information with their friends or acquaintances
Safety Technology	1	Offer user safety through monitoring and warning about potential risks in their surroundings
Gaming	4	Offer interactive entertainment through video games
Entertainment	2	Offer a range of digital media, including movies, music, and shows
E-Commerce	18	Offer online buying and selling of goods and services
Generic	15	Generalized category, allowing the effect to apply across multiple distinct platforms
Navigation	1	Offer geographic data and directions, helping users find routes and locations

Table C.7: Various platforms touched on in the literature corpus.

Appendix D

PRISMA 2020 Checklist

This appendix presents two checklists derived from the PRISMA Statement [Page et al., 2021], a comprehensive guideline for conducting systematic reviews and meta-analyses. The first checklist in Table D.1 assesses adherence to the 27 recommended items, with corresponding references to where each criterion has been addressed within the document.

The second checklist in Table D.2 mirrors this structure but is specifically tailored to evaluate the content of abstracts.

Section and Topic	Item #	Checklist Item	Location where item is reported
TITLE			
Title	1	Identify the report as a systematic review, meta-analysis, or both.	See Title
ABSTRACT			
Abstract	2	See the PRISMA 2020 for Abstracts checklist.	Table D.2

Continued on next page

Section and Topic	Item #	Checklist Item	Location where item is reported
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of what is already known.	Chapter 1.1
Objectives	4	Provide an explicit statement of the objective(s) or question(s) the review addresses.	Chapter 1.1
METHODS			
Eligibility criteria	5	Specify the inclusion and exclusion criteria for the review and how studies were grouped for the syntheses.	Chapter 3.1.2
Information sources	6	Specify all databases, registers, websites, organisations, reference lists and other sources searched or consulted to identify studies. Specify the date when each source was last searched or consulted.	Chapter 3.1.1
Search strategy	7	Present the full search strategies for all databases, registers and websites, including any filters and limits used.	Chapter 3.1.1
Selection process	8	Specify the methods used to decide whether a study met the inclusion criteria of the review, including how many reviewers screened each record and each report retrieved, whether they worked independently, and if applicable, details of automation tools used in the process.	Chapter 3.1.1, Chapter 3.1.2
Data collection process	9	Specify the methods used to collect data from reports, including how many reviewers collected data from each report, whether they worked independently, any processes for obtaining or confirming data from study investigators, and if applicable, details of automation tools used in the process.	Chapter 3.1.3

Continued on next page

Section and Topic	Item #	Checklist Item	Location where item is reported
Data items	10a	List and define all outcomes for which data were sought. Specify whether all results that were compatible with each outcome domain in each study were sought (e.g. for all measures, time points, analyses), and if not, the methods used to decide which results to collect.	Chapter 3.1.3
Data items	10b	List and define all other variables for which data were sought (e.g. participant and intervention characteristics, funding sources). Describe any assumptions made about any missing or unclear information.	Chapter 3.1.3
Study risk of bias assessment	11	Specify the methods used to assess risk of bias in the included studies, including details of the tool(s) used, how many reviewers assessed each study and whether they worked independently, and if applicable, details of automation tools used in the process.	Chapter 4.2
Effect measures	12	Specify for each outcome the effect measure(s) (e.g. risk ratio, mean difference) used in the synthesis or presentation of results.	Not Applicable (Literature was coded)
Synthesis methods	13a	Describe the processes used to decide which studies were eligible for each synthesis (e.g. tabulating the study intervention characteristics and comparing against the planned groups for each synthesis (item #5)).	Chapter 3.1.3
Synthesis methods	13b	Describe any methods required to prepare the data for presentation or synthesis, such as handling of missing summary statistics, or data conversions.	Chapter 3.1.3
Synthesis methods	13c	Describe any methods used to tabulate or visually display results of individual studies and syntheses.	Chapter 3.1.3

Continued on next page

Section and Topic	Item #	Checklist Item	Location where item is reported
Synthesis methods	13d	Describe any methods used to synthesize results and provide a rationale for the choice(s). If meta-analysis was performed, describe the model(s), method(s) to identify the presence and extent of statistical heterogeneity, and software package(s) used.	Chapter 3.1.3
Synthesis methods	13e	Describe any methods used to explore possible causes of heterogeneity among study results (e.g. subgroup analysis, meta-regression).	Not Done (Study results were only coded)
Synthesis methods	13f	Describe any sensitivity analyses conducted to assess robustness of the synthesized results.	Not Done (Study results were only coded)
Reporting bias assessment	14	Describe any methods used to assess risk of bias due to missing results in a synthesis (arising from reporting biases).	Chapter 3.1
Certainty assessment	15	Describe any methods used to assess certainty (or confidence) in the body of evidence for an outcome.	Not done
RESULTS			
Study selection	16a	Describe the results of the search and selection process, from the number of records identified in the search to the number of studies	Chapter 3.1, Figure 3.5
Study selection	16b	Cite studies that might appear to meet the inclusion criteria, but which were excluded, and explain why they were excluded.	Chapter 3.1
Study characteristics	17	Cite each included study and present its characteristics.	Appendix B
Risk of bias in studies	18	Present assessments of risk of bias for each included study.	Chapter 3.1

Continued on next page

Section and Topic	Item #	Checklist Item	Location where item is reported
Results of individual studies	19	For all outcomes, present, for each study: (a) summary statistics for each group (where appropriate) and (b) an effect estimate and its precision (e.g. confidence/credible interval), ideally using structured tables or plots.	Appendix B
Results of syntheses	20a	For each synthesis, briefly summarise the characteristics and risk of bias among contributing studies.	Not done
Results of syntheses	20b	Present results of all statistical syntheses conducted. If meta-analysis was done, present for each the summary estimate and its precision (e.g. confidence/credible interval) and measures of statistical heterogeneity. If comparing groups, describe the direction of the effect.	Chapter 3.2
Results of syntheses	20c	Present results of all investigations of possible causes of heterogeneity among study results.	Not done
Results of syntheses	20d	Present results of all sensitivity analyses conducted to assess the robustness of the synthesized results.	Not done
Reporting biases	21	Present assessments of risk of bias due to missing results (arising from reporting biases) for each synthesis assessed.	Chapter 4.2
Certainty of evidence	22	Present assessments of certainty (or confidence) in the body of evidence for each outcome assessed.	Not done
DISCUSSION			
Discussion	23a	Provide a general interpretation of the results in the context of other evidence.	Chapter 4.1
Discussion	23b	Discuss any limitations of the evidence included in the review.	Chapter 4.2
Discussion	23c	Discuss any limitations of the review processes used.	Chapter 4.2

Continued on next page

Section and Topic	Item #	Checklist Item	Location where item is reported
Discussion	23d	Discuss implications of the results for practice, policy, and future research.	Chapter 4.1.4, Chapter 5.2
OTHER INFORMATION			
Registration and protocol	24a	Provide registration information for the review, including register name and registration number, or state that the review was not registered.	Not applicable (Review within HCI)
Registration and protocol	24b	Indicate where the review protocol can be accessed, or state that a protocol was not prepared.	Not applicable (Review within HCI)
Registration and protocol	24c	Describe and explain any amendments to information provided at registration or in the protocol.	Not applicable (Review within HCI)
Support	25	Describe sources of financial or non-financial support for the review, and the role of the funders or sponsors in the review.	No financial support (non-sponsored thesis)
Competing interests	26	Declare any competing interests of review authors.	Chapter 2.1.4, Chapter 4.1
Availability of data, code and other materials	27	Report which of the following are publicly available and where they can be found: template data collection forms; data extracted from included studies; data used for all analyses; analytic code; any other materials used in the review.	Appendix A, Appendix B, Appendix C

Table D.1: The PRISMA 2020 statement consists of a 27-item checklist covering a systematic review report's introduction, methods, results, and discussion sections.

Section and Topic	Item #	Checklist Item	Reported (Yes/No)
TITLE			
Title	1	Identify the report as a systematic review, meta-analysis, or both.	Yes
BACKGROUND			
Back-ground	2	Provide an explicit statement of the main objective(s) or question(s) the review addresses.	Yes
METHODS			
Eligibility criteria	3	Specify the inclusion and exclusion criteria for the review.	Yes
Infor-mation sources	4	Specify the information sources (e.g. databases, registers) used to identify studies and the date when each was last searched.	Yes
Risk of bias	5	Specify the methods used to assess risk of bias in the included studies.	No (As no risk assess-ment was conducted)
Synthesis of results	6	Specify the methods used to present and synthesise results.	Yes
RESULTS			
Included studies	7	Give the total number of included studies and participants and summarise relevant characteristics of studies.	Yes
Synthesis of results	8	Present results for main outcomes, preferably indicating the number of included studies and participants for each. If meta-analysis was done, report the summary estimate and confidence/credible interval. If comparing groups, indicate the direction of the effect (i.e. which group is favoured).	Yes

Continued on next page

Section and Topic	Item #	Checklist Item	Reported (Yes/No)
DISCUSSION			
Limitations of evidence	9	Provide a brief summary of the limitations of the evidence included in the review (e.g. study risk of bias, inconsistency and imprecision).	Yes
Interpretation	10	Provide a general interpretation of the results and important implications.	Yes
OTHER			
Funding	11	Specify the primary source of funding for the review.	No (Non-sponsored thesis)
Registration	12	Provide the register name and registration number.	No (Review in HCI)

Table D.2: The 12-item checklist offers authors a structured guide to reduce their systematic review into the core elements required for an abstract.

Bibliography

[1] *CHI '24: Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems*, New York, NY, USA, 2024. Association for Computing Machinery.

[2] Jacob Aagaard, Miria Emma Clausen Knudsen, Per Bækgaard, and Kevin Doherty. A Game of Dark Patterns: Designing Healthy, Highly-Engaging Mobile Games. In *Extended Abstracts of the 2022 CHI Conference on Human Factors in Computing Systems*, CHI EA '22, New York, NY, USA, 2022. Association for Computing Machinery. doi.org/10.1145/3491101.3519837.

[3] Sanju Ahuja and Jyoti Kumar. Understanding Ethical Thinking in Design Education: A Linkographic Study. In *Proceedings of the 6th Annual Symposium on HCI Education*, EduCHI '24, New York, NY, USA, 2024. Association for Computing Machinery. doi.org/10.1145/3658619.3658620.

[4] Ishmael P. Akaah and Edward A. Riordan. The incidence of unethical practices in marketing research: An empricial investigation. *Journal of the Academy of Marketing Science*, 18(2):143–152, 1990. doi.org/10.1007/BF02726430.

[5] Lize Alberts, Ulrik Lyngs, and Max Van Kleek. Computers as Bad Social Actors: Dark Patterns and Anti-Patterns in Interfaces that Act Socially. *Proc. ACM Hum.-Comput. Interact.*, 8(CSCW1), April 2024. doi.org/10.1145/3653693.

[6] Nathalia Freire Albuquerque, George Valença, and Taciana Pontual Falcão. How Social Media Platforms Manipulate Kidinfluencers? Analysing the Adoption of Deceptive Design Patterns by Big Techs. In *Proceedings of the XXII Brazilian Symposium on Human Factors in Computing Systems*, IHC '23, New York, NY, USA, 2024. Association for Computing Machinery. doi.org/10.1145/3638067.3638123.

[7] Nadisha-Marie Aliman and Leon Kester. Malicious Design in AIVR, Falsehood and Cybersecurity-oriented Immersive Defenses. In *2020 IEEE International Conference on Artificial Intelligence and Virtual Reality (AIVR)*, pages 130–137, 2020. doi.org/10.1109/AIVR50618.2020.00031.

[8] Reza Ghaiumy Anaraky, Byron Lowens, Yao Li, Kaileigh A. Byrne, Marten Risius, Xinru Page, Pamela Wisniewski, Masoumeh Soleimani, Morteza Soltani, and Bart Knijnenburg. Older and younger adults are influenced differently by dark pattern designs, 2023. URL https://arxiv.org/abs/2310.03830.

[9] Esrnée Henrieke Anne de Haas and Lik-Hang Lee. Deceiving Audio Design in Augmented Environments : A Systematic Review of Audio Effects in Augmented Reality. In *2022 IEEE International Symposium on Mixed and Augmented Reality Adjunct (ISMAR-Adjunct)*, pages 36–43, 2022. doi.org/10.1109/ISMAR-Adjunct57072.2022.00018.

[10] Muneeba Asif, Mohammad Ashiqur Rahman, Kemal Akkaya, and Ahmad Mohammad. ConFIDe: A PWM-Driven Control-Fused Intrusion Detection System for Hardware Security in Unmanned Aerial Vehicles. In *Proceedings of the 19th ACM Asia Conference on Computer and Communications Security*, ASIA CCS '24, page 886–901, New York, NY, USA, 2024. Association for Computing Machinery. doi.org/10.1145/3634737.3657014.

[11] Vino Avanesi, Johanna Rockstroh, Thomas Mildner, Nima Zargham, Leon Reicherts, Maximilian A. Friehs, Dimosthenis Kontogiorgos, Nina Wenig, and Rainer Malaka. From C-3PO to HAL: Opening The Discourse About The Dark Side of Multi-Modal Social Agents. In *Proceedings of the 5th International Conference on Conversational User Interfaces*, CUI '23, New York, NY, USA, 2023. Association for Computing Machinery. doi.org/10.1145/3571884.3597441.

[12] Pooria Babaei and Julita Vassileva. Drivers and persuasive strategies to influence user intention to learn about manipulative design. In *Proceedings of the 2024 ACM Conference on Fairness, Accountability, and Transparency*, FAccT '24, page 2421–2431, New York, NY, USA, 2024. Association for Computing Machinery. doi.org/10.1145/3630106.3659046.

[13] Zakaria Babutsidze, Ann-Kathrin Blankenberg, and Andreas Chai. The effect of traditional media consumption and internet use on environmental attitudes in Europe. *Journal of Evolutionary Economics*, 33(2):309–340, 2023. doi.org/10.1007/s00191-023-00810-0.

[14] Luiz Adolpho Baroni, Alisson Andrey Puska, Luciana Cardoso de Castro Salgado, and Roberto Pereira. Dark Patterns: Towards a Socio-technical Approach. In *Proceedings of the XX Brazilian Symposium on Human Factors in Computing Systems*, IHC '21, New York, NY, USA, 2021. Association for Computing Machinery. doi.org/10.1145/3472301.3484336.

[15] Rosanna Bellini. Paying the Price: When Intimate Partners Use Technology for Financial Harm. In *Proceedings of the 2023 CHI Conference on Human Factors*

in Computing Systems, CHI '23, New York, NY, USA, 2023. Association for Computing Machinery. doi.org/10.1145/3544548.3581101.

[16] Benjamin Maximilian Berens, Heike Dietmann, Chiara Krisam, Oksana Kulyk, and Melanie Volkamer. Cookie Disclaimers: Impact of Design and Users' Attitude. In *Proceedings of the 17th International Conference on Availability, Reliability and Security*, ARES '22, New York, NY, USA, 2022. Association for Computing Machinery. doi.org/10.1145/3538969.3539008.

[17] Carlos Bermejo Fernandez, Dimitris Chatzopoulos, Dimitrios Papadopoulos, and Pan Hui. This Website Uses Nudging: MTurk Workers' Behaviour on Cookie Consent Notices. *Proc. ACM Hum.-Comput. Interact.*, 5(CSCW2), October 2021. doi.org/10.1145/3476087.

[18] Max V. Birk, Simone Van Der Hof, Celia Hodent, Kathrin Gerling, and Antonius J. Van Rooij. Behavioural Design in Video Games: Ethical, Legal, and Health Impact on Players. In *Extended Abstracts of the 2023 CHI Conference on Human Factors in Computing Systems*, CHI EA '23, New York, NY, USA, 2023. Association for Computing Machinery. doi.org/10.1145/3544549.3573801.

[19] Max V. Birk, Simone van der Hof, and Antonius J. van Rooij. Behavioral design in video games. *ACM Games*, 2(2), August 2024. doi.org/10.1145/3672088.

[20] Kerstin Bongard-Blanchy, Arianna Rossi, Salvador Rivas, Sophie Doublet, Vincent Koenig, and Gabriele Lenzini. "I am Definitely Manipulated, Even When I am Aware of it. It's Ridiculous!" - Dark Patterns from the End-User Perspective. In *Proceedings of the 2021 ACM Designing Interactive Systems Conference*, DIS '21, page 763–776, New York, NY, USA, 2021. Association for Computing Machinery. doi.org/10.1145/3461778.3462086.

[21] Kerstin Bongard-Blanchy, Jean-Louis Sterckx, Arianna Rossi, Anastasia Sergeeva, Vincent Koenig, Salvador Rivas, and Verena Distler. Analysing the Influence of Loss-Gain Framing on Data Disclosure Behaviour: A Study on the Use Case of App Permission Requests. In *Proceedings of the 2023 European Symposium on Usable Security*, EuroUSEC '23, page 112–125, New York, NY, USA, 2023. Association for Computing Machinery. doi.org/10.1145/3617072.3617108.

[22] Martin Brenncke. Regulating Dark Patterns. *Notre Dame J. Int'l Comp. L.*, 14: 39, 2024.

[23] H. Brignull. *Deceptive Patterns: Exposing the Tricks Tech Companies Use to Control You*. Harry Brignull, 2023. ISBN 9781739454401.

[24] H Brignull, M Leiser, C Santos, and K Doshi. Deceptive patterns – user interfaces designed to trick you, 4 2023. URL https://www.deceptive.design/.

[25] Christoph Bösch, Benjamin Erb, Frank Kargl, Henning Kopp, and Stefan Pfattheicher. Tales from the Dark Side: Privacy Dark Strategies and Privacy Dark Patterns. *Proceedings on Privacy Enhancing Technologies*, 2016:237–254, 07 2016. doi.org/10.1515/popets-2016-0038.

[26] Ryan Calo. Digital market manipulation. *Geo. Wash. L. Rev.*, 82:995, 2013.

[27] Evan Caragay, Katherine Xiong, Jonathan Zong, and Daniel Jackson. Beyond Dark Patterns: A Concept-Based Framework for Ethical Software Design. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems*, CHI '24, New York, NY, USA, 2024. Association for Computing Machinery. doi.org/10.1145/3613904.3642781.

[28] Weichen Joe Chang, Katie Seaborn, and Andrew A. Adams. Theorizing Deception: A Scoping Review of Theory in Research on Dark Patterns and Deceptive Design. In *Extended Abstracts of the 2024 CHI Conference on Human Factors in Computing Systems*, CHI EA '24, New York, NY, USA, 2024. Association for Computing Machinery. doi.org/10.1145/3613905.3650997.

[29] Akash Chaudhary, Jaivrat Saroha, Kyzyl Monteiro, Angus G. Forbes, and Aman Parnami. "Are You Still Watching?": Exploring Unintended User Behaviors and Dark Patterns on Video Streaming Platforms. In *Proceedings of the 2022 ACM Designing Interactive Systems Conference*, DIS '22, page 776–791, New York, NY, USA, 2022. Association for Computing Machinery. doi.org/10.1145/3532106.3533562.

[30] Jieshan Chen, Jiamou Sun, Sidong Feng, Zhenchang Xing, Qinghua Lu, Xiwei Xu, and Chunyang Chen. Unveiling the Tricks: Automated Detection of Dark Patterns in Mobile Applications. In *Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology*, UIST '23, New York, NY, USA, 2023. Association for Computing Machinery. doi.org/10.1145/3586183.3606783.

[31] Waiman Cheung. The use of the World Wide Web for commercial purposes. *Industrial Management & Data Systems*, 98(4):172–177, 2024/09/08 1998. doi.org/10.1108/02635579810219345.

[32] Ishita Chordia, Lena-Phuong Tran, Tala June Tayebi, Emily Parrish, Sheena Erete, Jason Yip, and Alexis Hiniker. Deceptive Design Patterns in Safety Technologies: A Case Study of the Citizen App. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*, CHI '23, New York, NY, USA, 2023. Association for Computing Machinery. doi.org/10.1145/3544548.3581258.

[33] Gregory Conti and Edward Sobiesk. Malicious interface design: exploiting the user. In *Proceedings of the 19th International Conference on World Wide Web*,

WWW '10, page 271–280, New York, NY, USA, 2010. Association for Computing Machinery. doi.org/10.1145/1772690.1772719.

[34] Martin Degeling, Christine Utz, Christopher Lentzsch, Henry Hosseini, Florian Schaub, and Thorsten Holz. We Value Your Privacy ... Now Take Some Cookies. *Informatik Spektrum*, 42(5):345–346, 2019. doi.org/10.1007/s00287-019-01201-1.

[35] Maarten Denoo, Bruno Dupont, and Bieke Zaman. Many faces, many names? Ethics in Belgian game development education. *ACM Games*, 2(2), August 2024. doi.org/10.1145/3675804.

[36] Linda Di Geronimo, Larissa Braz, Enrico Fregnan, Fabio Palomba, and Alberto Bacchelli. UI Dark Patterns and Where to Find Them: A Study on Mobile Applications and User Perception. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, CHI '20, page 1–14, New York, NY, USA, 2020. Association for Computing Machinery. doi.org/10.1145/3313831.3376600.

[37] Rod Dickinson, Nathan Semertzidis, and Florian Floyd Mueller. Machine In The Middle: Exploring Dark Patterns of Emotional Human-Computer Integration Through Media Art. In *Extended Abstracts of the 2022 CHI Conference on Human Factors in Computing Systems*, CHI EA '22, New York, NY, USA, 2022. Association for Computing Machinery. doi.org/10.1145/3491101.3503555.

[38] Jeevan D'Souza and C Adams. Towards a Humanistic Definition of Greed. *American International Journal of Social Science*, 5:9–12, 06 2016.

[39] Mateusz Dubiel, Anastasia Sergeeva, and Luis A. Leiva. Impact of Voice Fidelity on Decision Making: A Potential Dark Pattern? In *Proceedings of the 29th International Conference on Intelligent User Interfaces*, IUI '24, page 181–194, New York, NY, USA, 2024. Association for Computing Machinery. doi.org/10.1145/3640543.3645202.

[40] Elizabeth Dula, Andres Rosero, and Elizabeth Phillips. Identifying Dark Patterns in Social Robot Behavior. In *2023 Systems and Information Engineering Design Symposium (SIEDS)*, pages 7–12, 2023. doi.org/10.1109/SIEDS58326.2023.10137912.

[41] Chloe Eghtebas, Gudrun Klinker, Susanne Boll, and Marion Koelle. Co-Speculating on Dark Scenarios and Unintended Consequences of a Ubiquitous(ly) Augmented Reality. In *Proceedings of the 2023 ACM Designing Interactive Systems Conference*, DIS '23, page 2392–2407, New York, NY, USA, 2023. Association for Computing Machinery. doi.org/10.1145/3563657.3596073.

[42] Jiaying Feng, Fan Mo, Yuki Yada, Tsuneo Matsumoto, Nao Fukushima, Fukuyo Kido, and Hayato Yamana. Analysis of Dark Pattern-related Tweets

from 2010. In *2023 IEEE 8th International Conference on Big Data Analytics (ICBDA)*, pages 100–106, 2023. doi.org/10.1109/ICBDA57405.2023.10104855.

[43] Dan Fitton, Scott MacKenzie, and Janet Read. Investigating the Impact of Monetization on Children's Experience With Mobile Games. In *Proceedings of the 23rd Annual ACM Interaction Design and Children Conference*, IDC '24, page 248–258, New York, NY, USA, 2024. Association for Computing Machinery. doi.org/10.1145/3628516.3655794.

[44] B. J. Fogg. Persuasive technology: using computers to change what we think and do. *Ubiquity*, 2002(December), dec 2002. doi.org/10.1145/764008.763957.

[45] Guo Freeman, Karen Wu, Nicholas Nower, and Donghee Yvette Wohn. Pay to Win or Pay to Cheat: How Players of Competitive Online Games Perceive Fairness of In-Game Purchases. *Proc. ACM Hum.-Comput. Interact.*, 6(CHI PLAY), October 2022. doi.org/10.1145/3549510.

[46] Myriam Frejus, Julien Guibourdenche, and Dominique Martini. Contextualité des questions de privacy dans l'utilisation de services interactifs et conséquences pour la conception: The Contextuality of Privacy Issues in Interactive Services, and its Consequences for Design. In *Proceedings of the 34th Conference on l'Interaction Humain-Machine*, IHM '23, New York, NY, USA, 2023. Association for Computing Machinery. doi.org/10.1145/3583961.3583970.

[47] Julian Frommel, Guo Freeman, Janelle E. MacKenzie, Daniel Johnson, and Regan L. Mandryk. Workshop on Understanding and Combating the Problematic Side of Play. In *Companion Proceedings of the Annual Symposium on Computer-Human Interaction in Play*, CHI PLAY Companion '23, page 348–349, New York, NY, USA, 2023. Association for Computing Machinery. doi.org/10.1145/3573382.3616025.

[48] Paul Grassl, Hanna Schraffenberger, Frederik Zuiderveen Borgesius, and Moniek Buijzen. Dark and bright patterns in cookie consent requests, Jul 2020. URL osf.io/preprints/psyarxiv/gqs5h.

[49] Colin M. Gray, Yubo Kou, Bryan Battles, Joseph Hoggatt, and Austin L. Toombs. The Dark (Patterns) Side of UX Design. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, CHI '18, page 1–14, New York, NY, USA, 2018. Association for Computing Machinery. doi.org/10.1145/3173574.3174108.

[50] Colin M. Gray, Shruthi Sai Chivukula, and Ahreum Lee. What Kind of Work Do "Asshole Designers" Create? Describing Properties of Ethical Concern on

Reddit. In *Proceedings of the 2020 ACM Designing Interactive Systems Conference*, DIS '20, page 61–73, New York, NY, USA, 2020. Association for Computing Machinery. doi.org/10.1145/3357236.3395486.

[51] Colin M. Gray, Jingle Chen, Shruthi Sai Chivukula, and Liyang Qu. End User Accounts of Dark Patterns as Felt Manipulation. *Proc. ACM Hum.-Comput. Interact.*, 5(CSCW2), October 2021. doi.org/10.1145/3479516.

[52] Colin M. Gray, Shruthi Sai Chivukula, Kassandra Melkey, and Rhea Manocha. Understanding "Dark" Design Roles in Computing Education. In *Proceedings of the 17th ACM Conference on International Computing Education Research*, ICER 2021, page 225–238, New York, NY, USA, 2021. Association for Computing Machinery. doi.org/10.1145/3446871.3469754.

[53] Colin M. Gray, Cristiana Santos, Nataliia Bielova, Michael Toth, and Damian Clifford. Dark Patterns and the Legal Requirements of Consent Banners: An Interaction Criticism Perspective. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, CHI '21, New York, NY, USA, 2021. Association for Computing Machinery. doi.org/10.1145/3411764.3445779.

[54] Colin M. Gray, Shruthi Sai Chivukula, Kerstin Bongard-Blanchy, Arunesh Mathur, Johanna T. Gunawan, and Brennan Schaffner. Emerging Transdisciplinary Perspectives to Confront Dark Patterns. In *Extended Abstracts of the 2023 CHI Conference on Human Factors in Computing Systems*, CHI EA '23, New York, NY, USA, 2023. Association for Computing Machinery. doi.org/10.1145/3544549.3583745.

[55] Colin M. Gray, Lorena Sanchez Chamorro, Ike Obi, and Ja-Nae Duane. Mapping the Landscape of Dark Patterns Scholarship: A Systematic Literature Review. In *Companion Publication of the 2023 ACM Designing Interactive Systems Conference*, DIS '23 Companion, page 188–193, New York, NY, USA, 2023. Association for Computing Machinery. doi.org/10.1145/3563703.3596635.

[56] Colin M. Gray, Cristiana Santos, and Nataliia Bielova. Towards a Preliminary Ontology of Dark Patterns Knowledge. In *Extended Abstracts of the 2023 CHI Conference on Human Factors in Computing Systems*, CHI EA '23, New York, NY, USA, 2023. Association for Computing Machinery. doi.org/10.1145/3544549.3585676.

[57] Colin M. Gray, Cristiana Teixeira Santos, Nicole Tong, Thomas Mildner, Arianna Rossi, Johanna T. Gunawan, and Caroline Sinders. Dark Patterns and the Emerging Threats of Deceptive Design Practices. In *Extended Abstracts of the 2023 CHI Conference on Human Factors in Computing Systems*, CHI EA '23, New York, NY, USA, 2023. Association for Computing Machinery. doi.org/10.1145/3544549.3583173.

[58] Colin M. Gray, Ritika Gairola, Nayah Boucaud, Maliha Hashmi, Shruthi Sai Chivukula, Ambika R Menon, and Ja-Nae Duane. Legal Trouble?: UX Practitioners' Engagement with Law and Regulation. In *Companion Publication of the 2024 ACM Designing Interactive Systems Conference*, DIS '24 Companion, page 106–110, New York, NY, USA, 2024. Association for Computing Machinery. doi.org/10.1145/3656156.3663698.

[59] Colin M. Gray, Johanna T. Gunawan, René Schäfer, Nataliia Bielova, Lorena Sanchez Chamorro, Katie Seaborn, Thomas Mildner, and Hauke Sandhaus. Mobilizing Research and Regulatory Action on Dark Patterns and Deceptive Design Practices. In *Extended Abstracts of the 2024 CHI Conference on Human Factors in Computing Systems*, CHI EA '24, New York, NY, USA, 2024. Association for Computing Machinery. doi.org/10.1145/3613905.3636310.

[60] Colin M. Gray, Cristiana Teixeira Santos, Nataliia Bielova, and Thomas Mildner. An Ontology of Dark Patterns Knowledge: Foundations, Definitions, and a Pathway for Shared Knowledge-Building. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*, CHI '24, New York, NY, USA, 2024. Association for Computing Machinery. doi.org/10.1145/3613904.3642436.

[61] Johanna Gunawan, Amogh Pradeep, David Choffnes, Woodrow Hartzog, and Christo Wilson. A Comparative Study of Dark Patterns Across Web and Mobile Modalities. *Proc. ACM Hum.-Comput. Interact.*, 5(CSCW2), oct 2021. doi.org/10.1145/3479521.

[62] Johanna Gunawan, Cristiana Santos, and Irene Kamara. Redress for Dark Patterns Privacy Harms? A Case Study on Consent Interactions. In *Proceedings of the 2022 Symposium on Computer Science and Law*, CSLAW '22, page 181–194, New York, NY, USA, 2022. Association for Computing Machinery. doi.org/10.1145/3511265.3550448.

[63] Ralf Gundelach and Dominik Herrmann. Cookiescanner: An Automated Tool for Detecting and Evaluating GDPR Consent Notices on Websites. In *Proceedings of the 18th International Conference on Availability, Reliability and Security*, ARES '23, New York, NY, USA, 2023. Association for Computing Machinery. doi.org/10.1145/3600160.3605000.

[64] Hana Habib, Megan Li, Ellie Young, and Lorrie Cranor. "Okay, whatever": An Evaluation of Cookie Consent Interfaces. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*, CHI '22, New York, NY, USA, 2022. Association for Computing Machinery. doi.org/10.1145/3491102.3501985.

[65] Hilda Hadan, Lydia Choong, Leah Zhang-Kennedy, and Lennart E. Nacke. Deceived by Immersion: A Systematic Analysis of Deceptive Design in Ex-

tended Reality. *ACM Comput. Surv.*, 56(10), May 2024. doi.org/10.1145/3659945.

[66] Ayah Hamad and Bochen Jia. How virtual reality technology has changed our lives: an overview of the current and potential applications and limitations. *International journal of environmental research and public health*, 19(18): 11278, 2022.

[67] Jon D Hanson and Douglas A Kysar. Taking behavioralism seriously: The problem of market manipulation. *NYUL rev.*, 74:630, 1999.

[68] Shun Hidaka, Sota Kobuki, Mizuki Watanabe, and Katie Seaborn. Linguistic Dead-Ends and Alphabet Soup: Finding Dark Patterns in Japanese Apps. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*, CHI '23, New York, NY, USA, 2023. Association for Computing Machinery. doi.org/10.1145/3544548.3580942.

[69] Celia Hodent, Fran Blumberg, and Sebastian Deterding. Ethical Games: Toward Evidence-Based Guidance for Safeguarding Players and Developers. *ACM Games*, 2(2), August 2024. doi.org/10.1145/3685207.

[70] Mairéad Hogan, Chris Barry, and Michael Lang. Dissecting Optional Micro-Decisions in Online Transactions: Perceptions, Deceptions, and Errors. *ACM Trans. Comput.-Hum. Interact.*, 29(6), November 2022. doi.org/10.1145/3531005.

[71] Hsiu-Fang Hsieh and Sarah E. Shannon. Three Approaches to Qualitative Content Analysis. *Qualitative Health Research*, 15(9):1277–1288, 2005. doi.org/10.1177/1049732305276687. PMID: 16204405.

[72] Yavuz Inal, Frode S. Volden, Camilla Carlsen, and Sarah Hjelmtveit. My Eyes Don't Consent! Exploring Visual Attention in Cookie Consent Interfaces. In *Proceedings of the 2024 Symposium on Eye Tracking Research and Applications*, ETRA '24, New York, NY, USA, 2024. Association for Computing Machinery. doi.org/10.1145/3649902.3653352.

[73] Elaheh Jafari and Julita Vassileva. Designing Effective Warnings for Manipulative Designs in Mobile Applications. In *Proceedings of the 32nd ACM Conference on User Modeling, Adaptation and Personalization*, UMAP '24, page 12–17, New York, NY, USA, 2024. Association for Computing Machinery. doi.org/10.1145/3627043.3659550.

[74] Maya A Kaneko, Caitlin Lustig, Daniela Rosner, and Audrey Desjardins. Care Layering: Complicating Design Patterns. In *Proceedings of the 2024 ACM Designing Interactive Systems Conference*, DIS '24, page 1533–1546, New York, NY, USA, 2024. Association for Computing Machinery. doi.org/10.1145/3643834.3660740.

[75] Maxwell Keleher, Fiona Westin, Preethi Nagabandi, and Sonia Chiasson. How Well Do Experts Understand End-Users' Perceptions of Manipulative Patterns? In *Nordic Human-Computer Interaction Conference*, NordiCHI '22, New York, NY, USA, 2022. Association for Computing Machinery. doi.org/10.1145/3546155.3546656.

[76] Kay Kender and Christopher Frauenberger. The Shape of Social Media: Towards Addressing (Aesthetic) Design Power. In *Proceedings of the 2022 ACM Designing Interactive Systems Conference*, DIS '22, page 365–376, New York, NY, USA, 2022. Association for Computing Machinery. doi.org/10.1145/3532106.3533470.

[77] Khalid S Khan, Gerben Ter Riet, Julie Glanville, Amanda J Sowden, Jos Kleijnen, and others. *Undertaking systematic reviews of research on effectiveness: CRD's guidance for carrying out or commissioning reviews*. Number 4 (2n. NHS Centre for Reviews and Dissemination, 2001.

[78] John King, Dan Fitton, and Brendan Cassidy. Investigating Players' Perceptions of Deceptive Design Practices within a 3D Gameplay Context. *Proc. ACM Hum.-Comput. Interact.*, 7(CHI PLAY), October 2023. doi.org/10.1145/3611053.

[79] Daniel Kirkman, Kami Vaniea, and Daniel W. Woods. DarkDialogs: Automated detection of 10 dark patterns on cookie dialogs. In *2023 IEEE 8th European Symposium on Security and Privacy (EuroSP)*, pages 847–867, 2023. doi.org/10.1109/EuroSP57164.2023.00055.

[80] Barbara Kitchenham and Stuart Charters. Guidelines for performing Systematic Literature Reviews in Software Engineering. 2, 01 2007.

[81] Konrad Kollnig, Siddhartha Datta, and Max Van Kleek. I Want My App That Way: Reclaiming Sovereignty Over Personal Devices. In *Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems*, CHI EA '21, New York, NY, USA, 2021. Association for Computing Machinery. doi.org/10.1145/3411763.3451632.

[82] Konrad Kollnig, Siddhartha Datta, Thomas Serban Von Davier, Max Van Kleek, Reuben Binns, Ulrik Lyngs, and Nigel Shadbolt. 'We are adults and deserve control of our phones': Examining the risks and opportunities of a right to repair for mobile apps. In *Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency*, FAccT '23, page 22–34, New York, NY, USA, 2023. Association for Computing Machinery. doi.org/10.1145/3593013.3593973.

[83] Mariliza Kontogeorgou, Christof Van Nimwegen, and Almila Akdag Salah. Illuminating Muscle Memory's Sinister Side: A Social Media Case Study. In

Proceedings of the European Conference on Cognitive Ergonomics 2023, ECCE '23, New York, NY, USA, 2023. Association for Computing Machinery. doi.org/10.1145/3605655.3605664.

[84] Monica Kowalczyk, Johanna T. Gunawan, David Choffnes, Daniel J Dubois, Woodrow Hartzog, and Christo Wilson. Understanding Dark Patterns in Home IoT Devices. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*, CHI '23, New York, NY, USA, 2023. Association for Computing Machinery. doi.org/10.1145/3544548.3581432.

[85] Veronika Krauß, Pejman Saeghe, Alexander Boden, Mohamed Khamis, Mark McGill, Jan Gugenheimer, and Michael Nebeling. What Makes XR Dark? Examining Emerging Dark Patterns in Augmented and Virtual Reality through Expert Co-Design. *ACM Trans. Comput.-Hum. Interact.*, 31(3), aug 2024. doi.org/10.1145/3660340.

[86] Chiara Krisam, Heike Dietmann, Melanie Volkamer, and Oksana Kulyk. Dark Patterns in the Wild: Review of Cookie Disclaimer Designs on Top 500 German Websites. In *Proceedings of the 2021 European Symposium on Usable Security*, EuroUSEC '21, page 1–8, New York, NY, USA, 2021. Association for Computing Machinery. doi.org/10.1145/3481357.3481516.

[87] Lin Kyi, Sushil Ammanaghatta Shivakumar, Cristiana Teixeira Santos, Franziska Roesner, Frederike Zufall, and Asia J. Biega. Investigating Deceptive Design in GDPR's Legitimate Interest. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*, CHI '23, New York, NY, USA, 2023. Association for Computing Machinery. doi.org/10.1145/3544548.3580637.

[88] Cherie Lacey and Catherine Caudwell. Cuteness as a 'dark pattern' in home robots. In *Proceedings of the 14th ACM/IEEE International Conference on Human-Robot Interaction*, HRI '19, page 374–381. IEEE Press, 2020.

[89] Diana S. Lindblom, Marieke van Otterdijk, and Jim Torresen. A Qualitative Observational Video-Based Study on Perceived Privacy in Social Robots' Based on Robots Appearances. In *2024 IEEE International Conference on Advanced Robotics and Its Social Impacts (ARSO)*, pages 74–79, 2024. doi.org/10.1109/ARSO60199.2024.10557941.

[90] Mengyi Long, Yue Xu, Jiangrong Wu, Qihua Ou, and Yuhong Nan. Understanding Dark UI Patterns in the Mobile Ecosystem: A Case Study of Apps in China. In *Proceedings of the 2023 ACM Workshop on Secure and Trustworthy Superapps*, SaTS '23, page 33–40, New York, NY, USA, 2023. Association for Computing Machinery. doi.org/10.1145/3605762.3624431.

[91] Yuwen Lu, Chao Zhang, Yuewen Yang, Yaxing Yao, and Toby Jia-Jun Li. From Awareness to Action: Exploring End-User Empowerment Interventions for Dark Patterns in UX. *Proc. ACM Hum.-Comput. Interact.*, 8(CSCW1), April 2024. doi.org/10.1145/3637336.

[92] Jamie Luguri and Lior Jacob Strahilevitz. Shining a Light on Dark Patterns. *Journal of Legal Analysis*, 13(1):43–109, 03 2021. doi.org/10.1093/jla/laaa006.

[93] Kai Lukoff, Alexis Hiniker, Colin M. Gray, Arunesh Mathur, and Shruthi Sai Chivukula. What Can CHI Do About Dark Patterns? In *Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems*, CHI EA '21, New York, NY, USA, 2021. Association for Computing Machinery. doi.org/10.1145/3411763.3441360.

[94] Francisco Lupiáñez-Villanueva, Alba Boluda, Francesco Bogliacino, Giovanni Liva, Lucie Lechardoy, and Teresa Rodríguez de las Heras Ballell. *Behavioural study on unfair commercial practices in the digital environment – Dark patterns and manipulative personalisation – Final report*. Publications Office of the European Union, 2022. doi.org/doi/10.2838/859030.

[95] Aditi M. Bhoot, Mayuri A. Shinde, and Wricha P. Mishra. Towards the Identification of Dark Patterns: An Analysis Based on End-User Reactions. In *Proceedings of the 11th Indian Conference on Human-Computer Interaction*, IndiaHCI '20, page 24–33, New York, NY, USA, 2021. Association for Computing Machinery. doi.org/10.1145/3429290.3429293.

[96] S M Hasan Mansur. Toward Automated Tools to Support Ethical GUI Design. In *Proceedings of the 45th International Conference on Software Engineering: Companion Proceedings*, ICSE '23, page 294–298. IEEE Press, 2023. doi.org/10.1109/ICSE-Companion58688.2023.00079.

[97] S M Hasan Mansur, Sabiha Salma, Damilola Awofisayo, and Kevin Moran. AidUI: Toward Automated Recognition of Dark Patterns in User Interfaces. In *Proceedings of the 45th International Conference on Software Engineering*, ICSE '23, page 1958–1970. IEEE Press, 2023. doi.org/10.1109/ICSE48619.2023.00166.

[98] Arunesh Mathur. Identifying and Measuring Manipulative User Interfaces at Scale on the Web. In *Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems*, CHI EA '21, New York, NY, USA, 2021. Association for Computing Machinery. doi.org/10.1145/3411763.3457782.

[99] Arunesh Mathur, Gunes Acar, Michael J. Friedman, Eli Lucherini, Jonathan Mayer, Marshini Chetty, and Arvind Narayanan. Dark Patterns at Scale: Findings from a Crawl of 11K Shopping Websites. *Proc. ACM Hum.-Comput. Interact.*, 3(CSCW), nov 2019. doi.org/10.1145/3359183.

[100] Arunesh Mathur, Mihir Kshirsagar, and Jonathan Mayer. What Makes a Dark Pattern... Dark? Design Attributes, Normative Considerations, and Measurement Methods. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, CHI '21, New York, NY, USA, 2021. Association for Computing Machinery. doi.org/10.1145/3411764.3445610.

[101] Thomas Mejtoft, Nike Vejbrink Starbrink, Carla Roos Morales, Ole Norberg, Mattias Andersson, and Ulrik Söderström. Cookies and Trust: Trust in organizations and the design of cookie consent prompts. In *Proceedings of the European Conference on Cognitive Ergonomics 2023*, ECCE '23, New York, NY, USA, 2023. Association for Computing Machinery. doi.org/10.1145/3605655.3605668.

[102] Thomas Mildner and Gian-Luca Savino. Ethical User Interfaces: Exploring the Effects of Dark Patterns on Facebook. In *Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems*, CHI EA '21, New York, NY, USA, 2021. Association for Computing Machinery. doi.org/10.1145/3411763.3451659.

[103] Thomas Mildner, Philip Doyle, Gian-Luca Savino, and Rainer Malaka. Rules Of Engagement: Levelling Up To Combat Unethical CUI Design. In *Proceedings of the 4th Conference on Conversational User Interfaces*, CUI '22, New York, NY, USA, 2022. Association for Computing Machinery. doi.org/10.1145/3543829.3544528.

[104] Thomas Mildner, Merle Freye, Gian-Luca Savino, Philip R. Doyle, Benjamin R. Cowan, and Rainer Malaka. Defending Against the Dark Arts: Recognising Dark Patterns in Social Media. In *Proceedings of the 2023 ACM Designing Interactive Systems Conference*, DIS '23, page 2362–2374, New York, NY, USA, 2023. Association for Computing Machinery. doi.org/10.1145/3563657.3595964.

[105] Thomas Mildner, Gian-Luca Savino, Philip R. Doyle, Benjamin R. Cowan, and Rainer Malaka. About Engaging and Governing Strategies: A Thematic Analysis of Dark Patterns in Social Networking Services. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*, CHI '23, New York, NY, USA, 2023. Association for Computing Machinery. doi.org/10.1145/3544548.3580695.

[106] Thomas Mildner, Orla Cooney, Anna-Maria Meck, Marion Bartl, Gian-Luca Savino, Philip R Doyle, Diego Garaialde, Leigh Clark, John Sloan, Nina Wenig, Rainer Malaka, and Jasmin Niess. Listening to the Voices: Describing Ethical Caveats of Conversational User Interfaces According to Experts and Frequent Users. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems*, CHI '24, New York, NY, USA, 2024. Association for Computing Machinery. doi.org/10.1145/3613904.3642542.

[107] David Motta Miranda, Rebeca Maia Pontes, and Ticianne de Gois Ribeiro Darin. It's dark but just a game: towards an ethical and healthy game design practice. In *Proceedings of the 21st Brazilian Symposium on Human Factors in Computing Systems*, IHC '22, New York, NY, USA, 2022. Association for Computing Machinery. doi.org/10.1145/3554364.3559144.

[108] David Moher, Alessandro Liberati, Jennifer Tetzlaff, and Douglas Altman. Moher D, Liberati A, Tetzlaff J, Altman DG, Group PPreferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. PLoS Med 6: e1000097. *Open medicine : a peer-reviewed, independent, open-access journal*, 3:e123–30, 07 2009. doi.org/10.1016/j.jclinepi.2009.06.005.

[109] Alberto Monge Roffarello and Luigi De Russis. Towards Understanding the Dark Patterns That Steal Our Attention. In *Extended Abstracts of the 2022 CHI Conference on Human Factors in Computing Systems*, CHI EA '22, New York, NY, USA, 2022. Association for Computing Machinery. doi.org/10.1145/3491101.3519829.

[110] Alberto Monge Roffarello, Kai Lukoff, and Luigi De Russis. Defining and Identifying Attention Capture Deceptive Designs in Digital Interfaces. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*, CHI '23, New York, NY, USA, 2023. Association for Computing Machinery. doi.org/10.1145/3544548.3580729.

[111] Victor Morel, Cristiana Santos, Yvonne Lintao, and Soheil Human. Your Consent Is Worth 75 Euros A Year - Measurement and Lawfulness of Cookie Paywalls. In *Proceedings of the 21st Workshop on Privacy in the Electronic Society*, WPES'22, page 213–218, New York, NY, USA, 2022. Association for Computing Machinery. doi.org/10.1145/3559613.3563205.

[112] Arvind Narayanan, Arunesh Mathur, Marshini Chetty, and Mihir Kshirsagar. Dark Patterns: Past, Present, and Future: The evolution of tricky user interfaces. *Queue*, 18(2):67–92, may 2020. doi.org/10.1145/3400899.3400901.

[113] Dmitry Nazarov and Baimukhambetov Yerkebulan. Clustering of Dark Patterns in the User Interfaces of Websites and Online Trading Portals (E-Commerce). *Mathematics*, 10:3219, 09 2022. doi.org/10.3390/math10183219.

[114] Liming Nie, Yangyang Zhao, Chenglin Li, Xuqiong Luo, and Yang Liu. Shadows in the Interface: A Comprehensive Study on Dark Patterns. *Proc. ACM Softw. Eng.*, 1(FSE), July 2024. doi.org/10.1145/3643736.

[115] Katri Nousiainen and Catalina Perdomo Ortega. Dark Patterns in Law and Economics Framework. *Loy. Consumer L. Rev.*, 36:90, 2023.

[116] Midas Nouwens, Ilaria Liccardi, Michael Veale, David Karger, and Lalana Kagal. Dark Patterns after the GDPR: Scraping Consent Pop-ups and Demonstrating their Influence. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, CHI '20, page 1–13, New York, NY, USA, 2020. Association for Computing Machinery. doi.org/10.1145/3313831.3376321.

[117] OECD. Dark commercial patterns. (336), 2022. doi.org/https://doi.org/10.1787/44f5e846-en.

[118] Kentrell Owens, Johanna Gunawan, David Choffnes, Pardis Emami-Naeini, Tadayoshi Kohno, and Franziska Roesner. Exploring Deceptive Design Patterns in Voice Interfaces. In *Proceedings of the 2022 European Symposium on Usable Security*, EuroUSEC '22, page 64–78, New York, NY, USA, 2022. Association for Computing Machinery. doi.org/10.1145/3549015.3554213.

[119] Matthew J Page, Joanne E McKenzie, Patrick M Bossuyt, Isabelle Boutron, Tammy C Hoffmann, Cynthia D Mulrow, Larissa Shamseer, Jennifer M Tetzlaff, Elie A Akl, Sue E Brennan, Roger Chou, Julie Glanville, Jeremy M Grimshaw, Asbjørn Hróbjartsson, Manoj M Lalu, Tianjing Li, Elizabeth W Loder, Evan Mayo-Wilson, Steve McDonald, Luke A McGuinness, Lesley A Stewart, James Thomas, Andrea C Tricco, Vivian A Welch, Penny Whiting, and David Moher. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *BMJ*, 372, 2021. doi.org/10.1136/bmj.n71.

[120] Alexander Pfeiffer and Michaela Wawra. The Freedom of Choice Subtitle: A Preliminary Analysis of Lootboxes in EA FIFA Ultimate Team and the Introduction of a Player Type Model. 09 2023.

[121] Marie Potel-Saville and Mathilde Francois. From Dark Patterns to Fair Patterns? Usable Taxonomy to Contribute Solving the Issue with Countermeasures. 06 2023.

[122] Karen Renaud, Cigdem Sengul, Kovila Coopamootoo, Bryan Clift, Jacqui Taylor, Mark Springett, and Ben Morrison. "We're Not That Gullible!" Revealing Dark Pattern Mental Models of 11-12-Year-Old Scottish Children. *ACM Trans. Comput.-Hum. Interact.*, 31(3), August 2024. doi.org/10.1145/3660342.

[123] Yvonne Rogers, Paul Dourish, Patrick Olivier, Margot Brereton, and Jodi Forlizzi. The Dark Side of Interaction Design. In *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems*, CHI EA '20, page 1–4, New York, NY, USA, 2020. Association for Computing Machinery. doi.org/10.1145/3334480.3381070.

[124] Yvonne Rogers, Margot Brereton, Paul Dourish, Jodi Forlizzi, and Patrick Olivier. The Dark Side of Interaction Design. In *Extended Abstracts of the 2021*

CHI Conference on Human Factors in Computing Systems, CHI EA '21, New York, NY, USA, 2021. Association for Computing Machinery. doi.org/10.1145/3411763.3450397.

[125] Adinarayana Salina and Hrushikesava Raju Sangaraju. Smart dark pattern detection: Making aware of misleading patterns through the intended app. 06 2021.

[126] Lorena Sánchez Chamorro. Disentangling Online Manipulation Strategies from the Perspective of Digital Inequalities. In *Extended Abstracts of the 2023 CHI Conference on Human Factors in Computing Systems*, CHI EA '23, New York, NY, USA, 2023. Association for Computing Machinery. doi.org/10.1145/3544549.3577060.

[127] Lorena Sánchez Chamorro, Kerstin Bongard-Blanchy, and Vincent Koenig. Ethical Tensions in UX Design Practice: Exploring the Fine Line Between Persuasion and Manipulation in Online Interfaces. In *Proceedings of the 2023 ACM Designing Interactive Systems Conference*, DIS '23, page 2408–2422, New York, NY, USA, 2023. Association for Computing Machinery. doi.org/10.1145/3563657.3596013.

[128] Lorena Sánchez Chamorro, Romain Toebosch, and Carine Lallemand. Manipulative Design and Older Adults: Co-Creating Magic Machines to Understand Experiences of Online Manipulation. In *Proceedings of the 2024 ACM Designing Interactive Systems Conference*, DIS '24, page 668–684, New York, NY, USA, 2024a. Association for Computing Machinery. doi.org/10.1145/3643834.3661513.

[129] Lorena Sanchez Chamorro, Carine Lallemand, and Colin M. Gray. "My Mother Told Me These Things are Always Fake" - Understanding Teenagers' Experiences with Manipulative Designs. In *Proceedings of the 2024 ACM Designing Interactive Systems Conference*, DIS '24, page 1469–1482, New York, NY, USA, 2024b. Association for Computing Machinery. doi.org/10.1145/3643834.3660704.

[130] Hauke Sandhaus. Promoting Bright Patterns, 2023. URL https://arxiv.org/abs/2304.01157.

[131] Yasin Sazid, Mridha Md. Nafis Fuad, and Kazi Sakib. Automated Detection of Dark Patterns Using In-Context Learning Capabilities of GPT-3. In *2023 30th Asia-Pacific Software Engineering Conference (APSEC)*, pages 569–573, 2023. doi.org/10.1109/APSEC60848.2023.00072.

[132] René Schäfer, Paul Miles Preuschoff, and Jan Borchers. Investigating Visual Countermeasures Against Dark Patterns in User Interfaces. In *Proceedings of Mensch Und Computer 2023*, MuC '23, page 161–172, New York, NY, USA,

2023. Association for Computing Machinery. doi.org/10.1145/3603555.3603563.

[133] René Schäfer, Paul Miles Preuschoff, René Röpke, Sarah Sahabi, and Jan Borchers. Fighting Malicious Designs: Towards Visual Countermeasures Against Dark Patterns. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*, CHI '24, New York, NY, USA, 2024. Association for Computing Machinery. doi.org/10.1145/3613904.3642661.

[134] Brennan Schaffner, Neha A. Lingareddy, and Marshini Chetty. Understanding Account Deletion and Relevant Dark Patterns on Social Media. *Proc. ACM Hum.-Comput. Interact.*, 6(CSCW2), November 2022. doi.org/10.1145/3555142.

[135] Katie Seaborn, Tatsuya Itagaki, Mizuki Watanabe, Yijia Wang, Ping Geng, Takao Fujii, Yuto Mandai, Miu Kojima, and Suzuka Yoshida. Deceptive, Disruptive, No Big Deal: Japanese People React to Simulated Dark Commercial Patterns. In *Extended Abstracts of the 2024 CHI Conference on Human Factors in Computing Systems*, CHI EA '24, New York, NY, USA, 2024. Association for Computing Machinery. doi.org/10.1145/3613905.3651099.

[136] J Sharma. Dark Patterns in a Bright World: An Analysis of the Indian Consumer Legal Architecture. *IJCLP*, 11:123, 2023.

[137] Ashley Sheil, Gunes Acar, Hanna Schraffenberger, Raphael Gellert, and David Malone. Staying at the Roach Motel: Cross-Country Analysis of Manipulative Subscription and Cancellation Flows. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems*, CHI '24, New York, NY, USA, 2024. Association for Computing Machinery. doi.org/10.1145/3613904.3642881.

[138] Zewei Shi, Ruoxi Sun, Jieshan Chen, Jiamou Sun, and Minhui Xue. The Invisible Game on the Internet: A Case Study of Decoding Deceptive Patterns. In *Companion Proceedings of the ACM Web Conference 2024*, WWW '24, page 521–524, New York, NY, USA, 2024. Association for Computing Machinery. doi.org/10.1145/3589335.3651571.

[139] Ut Na Sio and Thomas Ormerod. Does Incubation Enhance Problem Solving? A Meta-Analytic Review. *Psychological bulletin*, 135:94–120, 01 2009. doi.org/10.1037/a0014212.

[140] Marnix Snel. *Doing a systematic literature review in legal scholarship*. 01 2018. ISBN 9462368074.

[141] Hannah Snyder. Literature review as a research methodology: An overview and guidelines. *Journal of Business Research*, 104:333–339, 2019. doi.org/10.1016/j.jbusres.2019.07.039.

[142] Than Htut Soe, Oda Elise Nordberg, Frode Guribye, and Marija Slavkovik. Circumvention by design - dark patterns in cookie consent for online news outlets. In *Proceedings of the 11th Nordic Conference on Human-Computer Interaction: Shaping Experiences, Shaping Society*, NordiCHI '20, New York, NY, USA, 2020. Association for Computing Machinery. doi.org/10.1145/3419249.3420132.

[143] Than Htut Soe, Cristiana Teixeira Santos, and Marija Slavkovik. Automated detection of dark patterns in cookie banners: how to do it poorly and why it is hard to do it any other way, 2022. URL https://arxiv.org/abs/2204.11836.

[144] Ioannis Stavrakakis, Andrea Curley, Dympna O'Sullivan, Damian Gordon, and Brendan Tierney. A Framework of Web-Based Dark Patterns that can be Detected Manually or Automatically. In *International Journal On Advances in Internet Technology*, volume 14. International Academy, Research, and Industry Association (IARIA), 2021. doi.org/10.21427/20G8-D176.

[145] Evropi Stefanidi, Marit Bentvelzen, Paweł W. Woźniak, Thomas Kosch, Mikołaj P. Woźniak, Thomas Mildner, Stefan Schneegass, Heiko Müller, and Jasmin Niess. Literature Reviews in HCI: A Review of Reviews. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*, CHI '23, New York, NY, USA, 2023. Association for Computing Machinery. doi.org/10.1145/3544548.3581332.

[146] Daniel Susser, Beate Roessler, and Helen Nissenbaum. Online Manipulation: Hidden Influences in a Digital World. *SSRN Electronic Journal*, 01 2018. doi.org/10.2139/ssrn.3306006.

[147] Michael Swart, Ylana Lopez, Arunesh Mathur, and Marshini Chetty. Is This An Ad?: Automatically Disclosing Online Endorsements On YouTube With AdIntuition. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, CHI '20, page 1–12, New York, NY, USA, 2020. Association for Computing Machinery. doi.org/10.1145/3313831.3376178.

[148] Mohammad Tahaei and Kami Vaniea. "Developers Are Responsible": Whatnbsp;Adnbsp;Networksnbsp;Tellnbsp;Developersnbsp;Aboutnbsp;Privacy. In *Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems*, CHI EA '21, New York, NY, USA, 2021. Association for Computing Machinery. doi.org/10.1145/3411763.3451805.

[149] Pumarin Tiangpanich and Apichaya Nimkoompai. An Analysis of Differences between Dark Pattern and Anti-Pattern to Increase Efficiency Application Design. In *2022 7th International Conference on Business and Industrial Research (ICBIR)*, pages 416–421, 2022. doi.org/10.1109/ICBIR54589.2022.9786470.

[150] Jelmer Tiemessen, Hanna Schraffenberger, and Gunes Acar. The Time is Ticking: The Effect of Limited Time Discounts on Consumers' Buying Behavior and Experience. In *Extended Abstracts of the 2023 CHI Conference on Human Factors in Computing Systems*, CHI EA '23, New York, NY, USA, 2023. Association for Computing Machinery. doi.org/10.1145/3544549.3585735.

[151] David Tranfield, David Denyer, and Palminder Smart. Towards a Methodology for Developing Evidence-Informed Management Knowledge by Means of Systematic Review. *British Journal of Management*, 14(3):207–222, 2003. doi.org/10.1111/1467-8551.00375.

[152] Marieke Van Hofslot, Almila Akdag Salah, Albert Gatt, and Cristiana Santos. Automatic Classification of Legal Violations in Cookie Banner Texts. In Nikolaos Aletras, Ilias Chalkidis, Leslie Barrett, Cătălina Goanță, and Daniel Preoțiuc-Pietro, editors, *Proceedings of the Natural Legal Language Processing Workshop 2022*, pages 287–295, Abu Dhabi, United Arab Emirates (Hybrid), December 2022. Association for Computational Linguistics. doi.org/10.18653/v1/2022.nllp-1.27.

[153] Maarten Van Mechelen, Gökçe Elif Baykal, Christian Dindler, Eva Eriksson, and Ole Sejer Iversen. 18 Years of ethics in child-computer interaction research: a systematic literature review. In *Proceedings of the Interaction Design and Children Conference*, IDC '20, page 161–183, New York, NY, USA, 2020. Association for Computing Machinery. doi.org/10.1145/3392063.3394407.

[154] Eszter Vigh, Angela Attwood, and Anne Roudaut. CounterSludge in Alcohol Purchasing on Online Grocery Shopping Platforms. In *Proceedings of the 2024 ACM Designing Interactive Systems Conference*, DIS '24, page 1741–1759, New York, NY, USA, 2024. Association for Computing Machinery. doi.org/10.1145/3643834.3661595.

[155] Ben Wagner, Krisztina Rozgonyi, Marie-Therese Sekwenz, Jennifer Cobbe, and Jatinder Singh. Regulating transparency? Facebook, Twitter and the German Network Enforcement Act. In *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency*, FAT* '20, page 261–271, New York, NY, USA, 2020. Association for Computing Machinery. doi.org/10.1145/3351095.3372856.

[156] Logan Warberg, Vincent Lefrere, Cristobal Cheyre, and Alessandro Acquisti. Trends in Privacy Dialog Design after the GDPR: The Impact of Industry and Government Actions. In *Proceedings of the 22nd Workshop on Privacy in the Electronic Society*, WPES '23, page 107–121, New York, NY, USA, 2023. Association for Computing Machinery. doi.org/10.1145/3603216.3624963.

[157] Barry Wellman, Anabel Quan-Haase, Jeffrey Boase, Wenhong Chen, Keith Hampton, Isabel Daz, and Kakuko Miyata. The Social Affordances of the

Internet for Networked Individualism. *Journal of Computer-Mediated Communication*, 8(3):JCMC834, 04 2003. doi.org/10.1111/j.1083-6101.2003.tb00216.x.

[158] Fiona Westin and Sonia Chiasson. Opt out of privacy or "go home": understanding reluctant privacy behaviours through the FoMO-centric design paradigm. In *Proceedings of the New Security Paradigms Workshop*, NSPW '19, page 57–67, New York, NY, USA, 2020. Association for Computing Machinery. doi.org/10.1145/3368860.3368865.

[159] Fiona Westin and Sonia Chiasson. "It's So Difficult to Sever that Connection": The Role of FoMO in Users' Reluctant Privacy Behaviours. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, CHI '21, New York, NY, USA, 2021. Association for Computing Machinery. doi.org/10.1145/3411764.3445104.

[160] Jacob Wobbrock and Julie Kientz. Research contribution in human-computer interaction. *interactions*, 23:38–44, 04 2016. doi.org/10.1145/2907069.

[161] Qunfang Wu, Yisi Sang, Dakuo Wang, and Zhicong Lu. Malicious Selling Strategies in Livestream E-commerce: A Case Study of Alibaba's Taobao and ByteDance's TikTok. *ACM Trans. Comput.-Hum. Interact.*, 30(3), June 2023. doi.org/10.1145/3577199.

[162] Yuki Yada, Jiaying Feng, Tsuneo Matsumoto, Nao Fukushima, Fuyuko Kido, and Hayato Yamana. Dark patterns in e-commerce: a dataset and its baseline evaluations. In *2022 IEEE International Conference on Big Data (Big Data)*, pages 3015–3022, 2022. doi.org/10.1109/BigData55660.2022.10020800.

[163] Yuki Yada, Tsuneo Matsumoto, Fuyuko Kido, and Hayato Yamana. Why is the User Interface a Dark Pattern?: Explainable Auto-Detection and its Analysis. In *2023 IEEE International Conference on Big Data (BigData)*, pages 6308–6310, 2023. doi.org/10.1109/BigData59044.2023.10386308.

[164] José Pablo Zagal, Staffan Björk, and Chris Lewis. Dark patterns in the design of games. In *International Conference on Foundations of Digital Games*, 2013.

[165] Eric Zeng, Miranda Wei, Theo Gregersen, Tadayoshi Kohno, and Franziska Roesner. Polls, clickbait, and commemorative $2 bills: problematic political advertising on news and media websites around the 2020 U.S. elections. In *Proceedings of the 21st ACM Internet Measurement Conference*, IMC '21, page 507–525, New York, NY, USA, 2021. Association for Computing Machinery. doi.org/10.1145/3487552.3487850.

[166] Leah Zhang-Kennedy, Maxwell Keleher, and Michaela Valiquette. Navigating the Gray: Design Practitioners' Perceptions Toward the Implementation

of Privacy Dark Patterns. *Proc. ACM Hum.-Comput. Interact.*, 8(CSCW1), April 2024. doi.org/10.1145/3637374.

[167] Nele Zielke. Exploring Dark Pattern Research within CHI: A Systematic Literature Review and Meta-Analysis. Bachelor's thesis, RWTH Aachen University, Aachen, March 2024.

Index

Typeset October 22, 2024